EVALUATING THE COSTS AND BENEFITS OF IMPLEMENTING A MARTA YOUTH FARE

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Kara Grace Todd

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EVALUATING THE COSTS AND BENEFITS OF IMPLEMENTING A MARTA YOUTH FARE

Approved by:

Dr. Patricia L. Mokhtarian, Advisor
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Catherine L. Ross
School of City and Regional Planning
Georgia Institute of Technology

Dr. Kari E. Watkins
School of Civil and Environmental Engineering
Georgia Institute of Technology

Dr. Giovanni Circella
School of Civil and Environmental Engineering
Georgia Institute of Technology

Date Approved: December 9, 2020

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LIST OF ABBREVIATIONS

MARTA	Metropolitan Atlanta Rapid Transit Authority
ARC	Atlanta Regional Commission
CTA	Chicago Transit Authority
Metro	Los Angeles County Metropolitan Transit Authority OR Washington Metropolitan Area Transit Authority
LIFE	Low Income Fare is Easy
ECC	Education Coordinating Council
MBTA	Massachusetts Bay Transportation Authority
DDOT	District Department of Transportation
SEPTA	Southeastern Pennsylvania Transportation Authority
NJ Transit	New Jersey Transit Corporation
Muni	San Francisco Municipal Transit Authority
BART	Bay Area Rapid Transit
ORCA	One Regional Card for All
TriMet	Tri-County Metropolitan Transportation District
AC Transit	Alameda-Contra Costa Transit District
HS	High School
MNL	Multinomial Logit
CBD	Central Business District
API	Application Programming Interface
GTFS	General Transit Feed Specifications

IVTT	In-vehicle travel time
OVTT	Out-of-vehicle travel time

SUMMARY

Unlike many transit systems in the United States, the Metropolitan Atlanta Rapid Transit Authority (MARTA) does not offer a discounted youth fare. Such a fare policy creates a financial disincentive to choosing transit for many families traveling with children or youth traveling independently. Instead, most parents chauffeur their children by car, adding to the well-known traffic congestion in the Atlanta region. Encouraging the use of more sustainable travel modes, including public transit, has benefits for the physical health of travelers as well as the economic and environmental well-being of the region.

The purpose of this research is to evaluate the costs and benefits, financial and otherwise, that might result if MARTA were to offer a reduced or even free youth fare. Using data from the 2011 Regional Household Travel Survey conducted by the Atlanta Regional Commission, a multinomial logit model of youth mode choice for non-school trips is developed. Various youth fare policies are then tested, including reduced and free fares for all youth as well as reduced and free fares available to only low-income youth, to estimate their potential to attract additional young riders. The policies are evaluated based on their estimated impacts on ridership and farebox revenue, as well as the socioeconomic characteristics of the individuals predicted to choose public transit in each scenario. Although offering a discounted youth fare may not be profitable to MARTA in the short-term, the positive impacts it could have on the community as a whole could outweigh the financial costs, making it worth further consideration by city and regional officials.

CHAPTER 1: INTRODUCTION

The Metropolitan Atlanta Rapid Transit Authority (MARTA) provides bus, rail, and paratransit service throughout the Atlanta region. Riders pay for their trips using either a single-use Breeze ticket or a refillable Breeze card (MARTA n.d.). MARTA charges most riders \$2.50 for a single trip but offers discounted fares of \$1 to senior citizens or riders with disabilities. Additionally, up to two children under 46 inches in height can ride for free with a paying adult (MARTA n.d.). Children reach this height at a median age of approximately six years, meaning that most older children and youth must pay the full adult fare to ride MARTA (National Center for Health Statistics and National Center for Chronic Disease Prevention and Health Promotion 2000a; 2000b). Unlike many transit systems in the United States, MARTA does not offer a discounted youth fare. Such a fare policy creates a financial disincentive to choosing transit for many families traveling with children or youth traveling independently.

The lack of affordable transit access for Atlanta youth means that parents are more likely to chauffeur their children by car, when available, or that children and youth without a vehicle in their household may simply be unable to make certain trips. Those who choose to travel by car contribute to Atlanta's well-known traffic congestion, a problem that city and regional leaders have been working for years to address. In 2019, Atlanta ranked as the 11th most congested city in the United States according to the INRIX Global Traffic Scorecard, with an estimated \$3 billion lost in passenger travel time and freight delays (Reed 2020). The 2013 Transportation Demand Management Plan produced by the Atlanta Regional Commission (ARC) acknowledged that encouraging the use of more sustainable modes, including public transit, is critical for the economic and environmental well-being of the region (Atlanta Regional Commission 2013). Reducing the fare that youth must pay to ride public transit in Atlanta is one way to incentivize such a mode shift and decrease the number of vehicles on the roads. Moreover, research has shown that those who travel on public transit as a child are more likely to continue to do so as an adult, suggesting that promoting youth transit ridership could reduce vehicle traffic, and the economic and environmental consequences that come with it, in both the short and long term (Long et al. 2019).

For children and teenagers without access to a vehicle or without an adult available to chauffeur them, the lack of affordable public transit can limit their opportunities for social and recreational activities and employment (Clifton 2003). Because low-income households are the most likely to be without a vehicle, removing financial barriers to transit has equity implications for the region. Improving access to public transit for these families may open up opportunities for low-income children and youth to participate in after-school educational or recreational programs, explore new parts of the city, or find employment in areas that would otherwise be difficult or impossible to access.

The purpose of this research was to evaluate the costs and benefits, financial and otherwise, that might result if MARTA were to offer a reduced or even free youth fare. Using data from the 2011 Regional Household Travel Survey conducted by the Atlanta Regional Commission (ARC), a multinomial logit model of youth mode choice for non-school trips was developed. Various youth fare policies were then tested on this model, including reduced and free fares for all youth as well as reduced and free fares available to only low-income youth, to estimate their potential to attract additional young riders. The policies were evaluated based on their estimated impacts on ridership and farebox revenue as well as the socioeconomic characteristics of the individuals predicted to choose public transit in each scenario. It is assumed that even if a fare policy is not predicted to be profitable to MARTA in the short-term, the positive impacts it could have on the environmental, economic, and social well-being of the region could outweigh the financial costs, making it worth further consideration by city and regional officials.

Chapter 2 discusses prior research on the travel behaviors of youth and their parents. Such studies have examined the factors that influence parental chauffeuring and independent youth travel, and the consequences that both mode choices can have on children's health, social life, awareness of their environment, and long-term travel behaviors. Chapter 3 provides examples of youth transit fare policies that have been implemented in cities across the United States, including eight of the ten largest transit systems in the country. Where available, the impact that these policies had on youth ridership and access to opportunities is described. An overview of the data and model used to evaluate the proposed MARTA youth fare policies is presented in Chapter 4. Chapter 5 contains the main portion of this research, describing first the current travel trends of youth and families in the Atlanta region and the details of MARTA's previous and current fare policies before presenting the results of the mode choice model under each proposed policy scenario. Based on the findings of this analysis, a recommended youth fare policy is described in Chapter 6, along with suggestions for the implementation of such a policy. Finally, a summary of the findings of this research and their implications for youth travel in Atlanta is presented in Chapter 7.

CHAPTER 2: BACKGROUND

Compared to research on adult travel behavior, relatively little work has been done to study children's travel patterns and mode choices. However, in recent years, the number of studies on children's travel appears to have increased as researchers have taken a growing interest in better understanding this fairly large demographic. This research includes both descriptive studies of the general travel trends of children and youth as well as models to assess which characteristics of households and the built environment influence these trends. Some of these studies focus on specific subareas of children's travel, including the influence of parents, the effects of children's independent mobility, and, especially relevant to the work presented here, youth transit ridership and fare policies. The sections below describe the findings of these studies, beginning with those that explored child and youth travel overall then focusing on the implications that childhood travel behavior and youth transit access have for health, equity, and long-term mode choices.

2.1 General Trends in Child, Youth, and Family Travel

One of the first major studies of children's travel was the work of Hillman, Adams, and Whitelegg (1990). This study looked at the travel of children ages seven to 15 in England and Germany and noted the decline in children's independent movement that began as early as the 1970's, as parents became more concerned with the dangers of traffic and strangers and chose to chauffeur their children. McDonald (2005a) described a similar decline in children's active and independent travel in the United States, as the proportion of students who walk or bike to school decreased from 42% to 13% between

1969 and 2005. This trend has been observed in many countries, to varying degrees. For example, the increased chauffeuring of British children noted by Hillman, Adams, and Whitelegg (1990) has continued into the 21st century; 53% of children's trips were taken by car in 2009 compared to only 35% in the 1980s (Mackett 2013). The proportion of children driven to school is also increasing in Denmark, Finland, and Norway, though it remains smaller than the shares observed in the United States and Great Britain (Fyhri et al. 2011).

The car-dependence of children has consequences for their physical health and social development, as well as larger-scale consequences for environmental sustainability and community equity. The decline in children's active travel and its implications for their health has been perhaps the largest motivator of studies in this field (Mackett 2013; McDonald 2005a). However, in working to understand the factors that prompt some parents to chauffeur their children, researchers have noted the role that socioeconomic status plays. Children and adolescents from low-income households or households with parents who are unemployed are less likely to be chauffeured, suggesting that they may lack the same access to opportunities that children and adolescents from higher-income households may be able to enjoy (Sener, Lee, and Sidharthan 2019; Bjerkan and Nordtømme 2014). An analysis of data from the 1995 National Personal Transportation Survey suggested that the association between access to a private vehicle and increased opportunity may continue even after youth have reached driving age, as the percentage of employed teens with a license (79.6%) was higher than the percentage of all teens with a license (66.8%) (Clifton 2003). Though this study points out that expenses associated with vehicle ownership may require the teen to seek employment, rather than employment requiring vehicle ownership, it is not unreasonable to suppose that access to a private vehicle may open up more opportunities for employment (Clifton 2003).

2.1.1. Parental Influence

The growing reliance on driving and chauffeuring among children and youth, and its range of consequences, have prompted a number of studies examining the factors that make parents more or less likely to chauffeur their children. Parents commonly cite concerns about traffic safety as one of the main reasons they chauffeur their children rather than allowing them to walk or bike, a mode choice that then ironically increases the traffic they see as an issue (Sener, Lee, and Sidharthan 2019; Fotel and Thomsen 2003; Carver, Timperio, and Crawford 2013). Unsurprisingly, the distance from home to school also seems to play a major role in motivating parents to drive their children, highlighting the important impact that school location policies have on children's travel (Woldeamanuel 2016; Yarlagadda and Srinivasan 2008; McDonald and Aalborg 2009). Finally, as mentioned above, parents' employment and income affect their ability to chauffeur their children. Studies of children's mode choice in the San Francisco area found that many parents value the convenience of dropping their children off at school on their way to work, especially mothers with inflexible work schedules, who presumably lack the time in the morning to accompany their children on foot (Yarlagadda and Srinivasan 2008; McDonald and Aalborg 2009). On the other hand, children from low-income households or with one or both parents unemployed are less likely to be chauffeured (Sener, Lee, and Sidharthan 2019; Bjerkan and Nordtømme 2014).

Though chauffeuring is the most direct way that parents influence their children's mode choice and travel behavior, researchers have found that parent attitudes and restrictions can also affect children's travel. In a study of Danish children's travel, parents reported supervising or controlling their children's mobility from afar by monitoring their location via GPS, requesting that they call upon reaching a certain location, or simply by restricting the routes that their children are allowed to take (Fotel and Thomsen 2003). Overall, parents' perceptions of the risk of allowing their children to travel independently, as well as their own schedules and mode choice, have a large influence on children's travel behavior, especially at a young age.

2.1.2. Independent Mobility Trends

The increased chauffeuring of children has equated to a decline in what researchers have termed children's "independent mobility" (Hillman, Adams, and Whitelegg 1990; Fyhri et al. 2011; Fyhri and Hjorthol 2009; Carver, Timperio, and Crawford 2013). Researchers have sought to better understand which factors contribute to children's independent mobility, a question that in some ways is simply another perspective on the studies of parental chauffeuring. The same factors that make parents more likely to chauffeur their children, including distance to school and concerns about traffic safety as discussed above, thus reduce the children's independent mobility (Carver, Timperio, and Crawford 2013; Yarlagadda and Srinivasan 2008). On the other hand, studies have found that children who are older or live in densely populated areas are more likely to travel independently via active modes, such as walking or cycling (Fyhri and Hjorthol 2009; Nelson et al. 2008). Parents who perceive their neighbors as likely to intervene should their children need assistance or behave in a way that requires discipline are also likely to grant their children more independent mobility (McDonald, Deakin, and Aalborg 2010). Finally, studies suggest that boys often have more freedom to travel independently than girls do, perhaps due to parents' differing perceptions of risk (Brown et al. 2008; Yarlagadda and Srinivasan 2008).

2.2 Impacts of Childhood and Youth Travel Patterns

Though understanding the factors that affect the travel behavior and mode choice of children and youth is helpful in designing policies to influence these decisions, especially when seeking to increase active travel and independence, it is also important to understand the far-reaching consequences that children's travel behavior can have. As mentioned above, one of the primary motivations for understanding children's mobility is concern over their physical health and the desire to promote active travel to help address this issue. Beyond the physical health benefits, though, traveling independently can help children and youth become more aware of their environment, give them opportunities to socialize with their peers, and may influence them to continue to use more active modes in adulthood.

2.2.1. Benefits of Independent Mobility

Studies of independent mobility have examined the behavior of both younger children and older teens. For younger children, traveling independently increases their understanding of their environment. In a study of Italian children who were asked to draw their journey to school on a blank map, children who traveled to school independently were able to more accurately reproduce their journeys than those who traveled with a guardian, either on foot or in a car (Rissotto and Tonucci 2002). As children age, their journeys begin to take on more social aspects. Many studies of teens' independent travel have been based in London, where a 2005 policy made bus travel free for youth ages 12 to 17, increasing the opportunities for many young people to travel without the need for a parental chauffeur (Jones et al. 2012). A common finding among these studies was that in addition to traveling to common destinations with friends, teens began to view the journey itself as a social activity (Jones et al. 2012; Goodman et al. 2014). Because of the flexibility offered by the free bus passes, focus group participants in these studies reported taking longer or more inconvenient routes or changing their travel plans to accommodate their friends (Goodman et al. 2014; Jones et al. 2012). Similar observations have been made about children and teens traveling on public transit in Sydney, where in addition to forgoing more efficient routes, these students often participated in games and group study activities during the journey (Symes 2007). Providing youth with an affordable and safe way to travel independently can thus help them develop wayfinding skills and offer greater opportunity to develop friendships with their peers.

2.2.2. Health Impacts of Increased Transit Use

Most studies of the physical health benefits of active travel have focused on entirely active modes, such as walking and biking, in comparison to entirely sedentary modes, such as driving or riding in a car, leaving the health impacts of transit relatively understudied (Jones et al. 2012). For example, one study examining the effects of walking to school in Britain found that children who walked to school instead of being driven burned more calories than they would with the recommended amount of physical activity and had more energy during their activities at their destinations (Mackett 2013). Because taking public transit almost always requires more walking during access and egress than does a journey by car but less physical activity than traveling entirely by walking or biking, it is difficult to predict the health consequences of promoting greater youth transit use.

Studies of youth transit use in London found that after the introduction of free bus passes in 2005, taking the bus replaced walking for many shorter trips because there was no financial downside (Edwards et al. 2013; Jones et al. 2012). However, it is also possible that some of these shorter trips may not have occurred at all if free transit were not an option, suggesting that overall physical activity may have actually increased as teens walked to and from bus stops (Jones et al. 2012). For longer trips, many survey participants reported that without free transit passes, they likely would have asked their parents to drive them or not traveled at all, again suggesting an increase in physical activity (Jones et al. 2012). Another study examined the amount of walking associated with public transit travel among American adults and found that the median time spent walking to and from transit was 19 minutes, with 29% of adult transit riders traveling more than 30 minutes by foot (Besser and Dannenberg 2005). Additionally, researchers in public health point out that the health benefits of free or more affordable transit for youth extend beyond the calories burned during the journey. A health impact assessment of implementing free youth transit in Los Angeles estimated that the policy could result in reduced vehicle emissions, improved environmental conditions, and reduced stress among students and their families (Gase et al. 2014). Though it's difficult to predict and quantify all health impacts of child and youth transit ridership, the evidence suggests that when the alternative is traveling by car, public transit offers benefits for the physical health of the riders and environmental health of their communities.

2.2.3. *Influence of Childhood Travel on Mode Choice in Adulthood*

Research on the relationship between travel behavior in childhood and adulthood is limited, largely due to the difficulties in collecting the longitudinal data needed to accurately assess whether a connection exists. However, because of the important policy implications of understanding travel behavior over time, a few researchers have worked to study these patterns by asking survey participants to recall characteristics of their built environment and travel behavior from childhood (Bou Mjahed, Frei, and Mahmassani 2015; Long et al. 2019). One of these studies, which was based on a survey of European adults, found that individuals who grew up with parents who had positive attitudes toward walking were more likely to walk frequently as adults and choose to live in more walkable areas. Similarly, their parents' attitudes toward car travel, the activity level of their peers, and the quality of their walk to school as a child had an impact on their travel behavior as adults (Bou Mjahed, Frei, and Mahmassani 2015). Another study highlighted the importance of bicycling experience at a young age in developing a positive attitude toward bicycling, which is likely to influence mode choice at later life stages (Thigpen and Handy 2018).

Fewer studies have looked at longitudinal travel behaviors associated with public transit. One study, using data from the 2014 Who's On Board Mobility Attitudes Survey in the U.S., found that while 55% of respondents who had traveled alone on public transit as a child continued to use transit in adulthood, only 43.3% of respondents who didn't travel on transit as a child used transit in adulthood, representing a significant correlation between childhood experience and adult transit use. A joint model of vehicle ownership and transit was then used to examine the effect sizes of direct childhood experiences and parental influences on each dependent variable and estimated that childhood experiences explained a very small portion of the propensity for vehicle ownership but accounted for 5% of the total variance in transit use, or 16% of the explained variance in transit use. Though this is a small portion compared to the variance explained by demographic and level of service variables, these results still show that there is a connection between exposure to transit as a child and choosing to travel on public transit in adulthood (Long et al. 2019).

2.3 Implications of Equitable Transit Access for Youth

As described above, children and teens who are from low-income households or households with parents who are unemployed are less likely to be chauffeured by their parents (Sener, Lee, and Sidharthan 2019; Bjerkan and Nordtømme 2014). Improving the affordability of transit could therefore offer an alternative for reaching destinations that are too far or too dangerous to bike or walk, especially for youth who may simply miss out on these opportunities otherwise. Research on the effects of implementing free transit for youth in Toronto found that the transit passes provided the students with increased opportunities, as 10% of survey respondents indicated that their recreational trips would not be possible without the pass (Sullivan 2017). Other work examining a similar policy in San Francisco found that while there was no significant change in school attendance in the first year of the reduced-fare program, there was an increase in participation in after-school activities. Additionally, they observed an increase in bus ridership among the students who received free bus passes (McDonald, Deakin, and Aalborg 2010). Some of the effects that free or reduced-price youth transit passes could have on improving equity in communities are more difficult to quantify. For example, public health researchers suggest that a free youth fare policy could have such far-reaching consequences as decreases in criminal activity, improvements in the mental health of students and their families, and a safer and cleaner environment in the communities, as it would eliminate fare evasion citations for youth and instead make it easier to access school and employment opportunities (Gase et al. 2014). These predictions likely wouldn't come to fruition in every community, especially those that implement reduced fares rather than free passes, but they demonstrate that the benefits of providing affordable transit to young people could extend beyond the realm that is traditionally considered in transportation planning.

CHAPTER 3: CASE STUDIES

Recognizing the benefits that could come from increasing youth transit access, cities across the United States and in other parts of the world have started offering free or reduced transit fares. When ranked by the number of unlinked passenger trips per year, MARTA was the 12th largest system in the United States in 2018, the most recent year for which data is available (American Public Transportation Association 2020). Among the 11 larger transit agencies, nine offer some sort of reduced fare for youth or students under 18. The sections below describe the youth fare policies of each of these agencies, as well as a few others. Where available, the impact that these policies have had on youth ridership is noted. Following the descriptions is a table summarizing the discounts offered by all of the agencies discussed in this chapter.

3.1 Chicago Transit Authority

Chicago Transit Authority (CTA) operates the 2nd largest system in the United States in terms of unlinked passenger trips (American Public Transportation Association 2020). CTA offers free fares to children under seven years of age and reduced fares for children ages seven to 11 at all times (Chicago Transit Authority 2020b). The reduced fare is $1.10 on buses and $1.25 on rail, compared to full fares of $2.25 on buses and $2.50 on rail (Chicago Transit Authority 2020a). Additionally, CTA offers even greater savings with student fares on school days between 5:30 AM and 8:30 PM, during which time both bus and rail fare is only $0.75 when paying with a Student Ventra Card. Students attending public schools receive a Student Ventra Card directly from their school while private school students can order a card from CTA through the mail, making the student fare program widely accessible.

3.2 Los Angeles County Metropolitan Transportation Authority

With around 75 million fewer annual trips than CTA, the Los Angeles County Metropolitan Transit Authority, or Metro, as it is commonly called, operates the 3rd largest system in the United States (American Public Transportation Association 2020). Students in kindergarten through 12th grade (under 21 years old) qualify for a reduced fare TAP card to use on the Metro system. This card allows them to take a one-way trip for \$1 or can be loaded with a 30-day pass for \$24. For low-income students, the cost of a monthly pass is further reduced to only \$14 (Los Angeles County Metropolitan Transportation Authority 2019b). In comparison, adults pay \$1.75 for a one-way trip or \$100 for a 30-day pass. Low-income adults qualify for the Low Income Fare is Easy (LIFE) program and can receive a 30-day pass for \$76 (Los Angeles County Metropolitan Transportation Authority 2019a). To receive a reduced-fare TAP card, students can apply online or in person at a Metro Customer Center, where they must prove their enrollment by showing a copy of a current report card, school ID, class schedule, or a letter from a school official (Los Angeles County Metropolitan Transportation Authority 2019b). When using this card to board Metro trains and buses, students in high school may be required to show a photo ID to prove eligibility for the reduced fare (Los Angeles County Metropolitan Transportation Authority 2019b).

In April 2013, the Los Angeles County Education Coordinating Council (ECC) proposed a policy to provide free transit passes to students in Los Angeles County in an effort to increase school attendance, as most districts in the county do not provide school buses to students (Gase et al. 2014). To estimate the impacts that such a policy might have, the ECC partnered with the Los Angeles County Department of Public Health to conduct a health impact assessment. This assessment predicted that offering free transit passes to students could result in an annual revenue loss of $71 million. However, researchers also suggested that in addition to increasing school attendance, the proposed policy had the potential to decrease student involvement with the juvenile justice system and improve the environmental health of their communities, as described in Chapter 2 (Gase et al. 2014). In the summer of 2019, the Los Angeles Department of Transportation began a one-year pilot program offering free rides on DASH buses to students in kindergarten through 12th grade who have a student TAP card (City of Los Angeles 2019b; 2019a). Though the effects of this program remain to be seen, the City of Los Angeles estimates it will result in a 10% increase in student ridership (City of Los Angeles 2019b).

3.3 Massachusetts Bay Transportation Authority – Boston, MA

The 4th largest transit operator in the United States, the Massachusetts Bay Transportation Authority (MBTA), also offers reduced fares for students through a program administered by middle and high schools (American Public Transportation Association 2020; Massachusetts Bay Transportation Authority n.d.). MBTA provides schools with the option of two different reduced-fare cards for their students: S-Cards and M7 Passes. With S-Cards, students add value themselves to pay reduced fares for one-way trips or may load the card with a discounted monthly pass (Massachusetts Bay Transportation Authority n.d.). These reduced fares are $1.10 for rail, $0.85 for bus, and $30 for a monthly pass, compared to full fares of $2.40 for rail, $1.79 for bus, and $90 for a similar monthly pass (Massachusetts Bay Transportation Authority n.d.; n.d.). Alternatively, middle and high schools can purchase M7 passes for $30 per month to provide their students with unlimited trips during the school year (Massachusetts Bay Transportation Authority n.d.). Additionally, all children 11 years old and younger can ride MBTA for free at any time (Massachusetts Bay Transportation Authority n.d.).

3.4 Washington Metropolitan Area Transit Authority – Washington, D.C

The next largest transit operator in the United States is the Washington Metropolitan Area Transit Authority (Metro), which allows students to travel for free through the Kids Ride Free program (American Public Transportation Association 2020; District Department of Transportation 2020b). In 1978, the District of Columbia passed the Student Transit Subsidy Act, which requires the District to allocate funds from its General Revenue Fund to the District Department of Transportation (DDOT) to provide reduced-fare transit passes to students (Vincent et al. 2014). The resulting Student Transit Subsidy program offered $30 monthly passes, which could be used for unlimited trips on Metrorail and Metrobus at all times, to students who live in D.C. and are under the age of 22 (Vincent et al. 2014).

In 2013, the D.C. City Council approved what was then known as the Ride Free on Bus program and is now called the Kids Ride Free program (Vincent et al. 2014; District Department of Transportation 2020b). The program originally allowed free travel for students on only weekdays between 5:30 and 9:30 AM and 2:00 and 8:00 PM but now provides free rides to and from school or related activities at any time (Vincent et al. 2014; District Department of Transportation 2020a). In comparison, the full fare for one ride on Metrobus is $2 and ranges from $2 to $6 on Metrorail, depending on origin and destination stations (Washington Metropolitan Area Transit Authority 2020a; 2020b) When the program first started, students were required to show their DC One card, which was also used to access school buildings and other public facilities, for all trips (Vincent et al. 2014). In the fall of 2018, the program began using SmarTrip cards, which are used by all Metro riders (Washington Metropolitan Area Transit Authority 2020c). The Kids Ride Free SmarTrip cards are administered through schools and are available to all students ages five to 21 who are enrolled in elementary or secondary schools, whether public or private, but not to college students (District Department of Transportation 2020b; 2020a).

3.5 Southeastern Pennsylvania Transportation Authority – Philadelphia, PA

The Southeastern Pennsylvania Transportation Authority (SEPTA) operates the 6th largest system in the United States in terms of unlinked passenger trips (American Public Transportation Association 2020). Similar to MBTA, SEPTA offers reduced fares for students but requires that the necessary passes be administered through the school district (Southeastern Pennsylvania Transportation Authority n.d.). If they choose, school districts can partner with SEPTA to sell their students weekday passes for $3.84 per day. These passes are good for unlimited trips between 5:30 AM and 7:00 PM on school days (Southeastern Pennsylvania Transportation Authority n.d.). A similar full-fare day pass is $9, and the full fare for a one-way trip is $2 (Southeastern Pennsylvania Transportation Authority n.d.). Though children under the age of 12 can travel for free with an adult, children of any age who are traveling alone must pay the full fare unless they have a school-administered Student Pass (Southeastern Pennsylvania Transportation Authority n.d.). Compared to the youth fare policies of other large transit systems in the United

States, the discounts that SEPTA offers to students are fairly limited but still provide a more affordable option than systems without any reduced fares for youth.

3.6 New Jersey Transit Corporation – Newark, NJ

With around 265 million annual passenger trips, the New Jersey Transit Corporation (NJ Transit) is the 7th largest system in the United States (American Public Transportation Association 2020). In a hybrid of the student fare administration strategies described above, NJ Transit sells reduced-fare passes directly to students and allows schools to purchase passes in bulk and sell them to their students (NJ Transit 2020). Students who choose to purchase their tickets directly from NJ Transit can do so at major bus terminals and must show a NJ Transit Student ID card issued by their school. The reduced fares are available to students in kindergarten through 12th grade and save them 33% on bus fares and 25% on light rail fares and monthly passes (NJ Transit 2020).

3.7 San Francisco Municipal Transit Agency and Bay Area Rapid Transit

The San Francisco Municipal Transit Agency (Muni) and Bay Area Rapid Transit (BART) represent the 8th and 11th largest systems in the United States, respectively (American Public Transportation Association 2020). Both Muni and BART use the Clipper Card payment system and offer discounted fares of $1.25 for a single ride or $40 for a monthly pass versus $2.50 for a full-fare single ride or $81 for a monthly pass for youth ages five to 18. Additionally, low-income youth can ride for free (San Francisco Municipal Transportation Agency 2020; Bay Area Rapid Transit 2020). Students can purchase a Youth Clipper card by mail, email, fax, or in person by providing identification with proof of age (Metropolitan Transportation Commission 2020).

3.8 King County Metro – Seattle, WA

King County Metro, the 10th largest system, offers discounted fares to all youth between the ages of six and 18 and free travel for high school students (King County Metro 2018; City of Seattle 2020). To receive the discounts, students may purchase ORCA youth cards through the mail or in person at a customer service center by proving their age with a school or state ID or birth certificate (King County Metro 2020). These cards allow youth to travel for $1.50 per ride compared to $2.75 for the full fare (King County Metro 2018). During the summer of 2017, King County Metro offered a pilot program during which students could ride buses for only $0.50 and rail for only $1 per ride, which resulted in a 35% increase in youth ridership. In a survey of 108 program participants, two-thirds reported riding transit more because of the reduced fare (Constantine 2017). Now, through the OCRA Opportunity Youth Program, high school students and some middle school students enrolled in Seattle Public Schools are eligible for unlimited free rides on King County Metro transit and Sound Transit. All public high school students can pick up a free ORCA card at their school at the beginning of the school year. Low-income middle school students or those who are not eligible for transportation through Seattle Public Schools also qualify for free ORCA cards, which are valid for one year (City of Seattle 2020).

3.9 Tri-County Metropolitan Transportation District of Oregon – Portland, OR

The Tri-County Metropolitan Transportation District, or TriMet, provides fewer rides per year than MARTA but still offers an interesting example of a youth fare policy (American Public Transportation Association 2020). TriMet offers half-price fares for youth ages seven to 17 at all times. Additionally, because the Portland Public School

District does not provide bus service, public high school students can ride TriMet for free during the school year through the Youth Pass program (TriMet 2020). The Youth Pass program began in 2008 and was originally funded through the Business Energy Tax Credit program. In 2011, the program was no longer eligible for these credits, so the City of Portland, Portland Public Schools, and TriMet began splitting the costs to continue the program (Vincent et al. 2014). The City then pulled out of this deal in 2018, but Portland Public Schools began paying the City's share of the estimated $2.9 million annual bill (Theen 2018). About 12,500 students take advantage of the Youth Pass each year (Vincent et al. 2014).

3.10 Alameda-Contra Costa Transit District – Oakland, CA

Alameda-Contra Costa Transit District (AC Transit) provides bus service in Oakland and other cities on the eastern side of the San Francisco Bay area (Vincent et al. 2014). Oakland Unified School District does not provide traditional yellow buses, so students are responsible for finding their own transportation to school (Vincent et al. 2014). In 2002, AC Transit began offering free bus passes to low-income youth and reduced-price ($15) monthly passes for all youth, with the goal of increasing school attendance and opportunities for after-school activities for low-income students (McDonald, Librera, and Deakin 2004). One year after the program's implementation, researchers found that while there was no significant change in school attendance, there was an increase in participation in after-school activities. Additionally, they observed an increase in bus ridership among the students who received free bus passes (McDonald, Librera, and Deakin 2004).

However, in 2003, the free youth fare program was discontinued due to budget constraints, requiring all youth to pay $15 for a monthly pass and offering an interesting example of the impact such a policy can have on ridership (McDonald 2005b). In the second year of the program, the percentage of students who rode AC Transit to school decreased from 27% to 24%. This decrease was largely reflective of the change in behavior of low-income students who had previously received a free pass: only 50% of these students rode AC Transit to school in the second year of the program compared to 70% in the first year (McDonald 2005b). Today, youth ages five to 18 pay half price for one-way trips and can purchase a monthly AC Transit pass for $34 compared to the $84.60 charged for adult monthly passes (Alameda-Contra Costa Transit District n.d.).

3.11 Summary

Although few of the agencies described above have examined or published the impacts of their youth fare policy on ridership and revenue, the studies available indicate that reduced or free fares lead to increased ridership. As mentioned, a study of the free and reduced transit passes offered by AC Transit showed that more students took transit to school when they had a free pass than when they had a reduced-fare pass (McDonald 2005b). Similar studies and surveys have shown that students made more transit trips when fares were reduced (Sullivan 2017; Constantine 2017). The table below summarizes the current youth fare policies of the agencies described in the preceding sections. In the interest of space, the agencies are listed by their shorter and more commonly used names, rather than the official agency title.

Table 1: *Comparison of full fares and youth/student fares*

Agency	City/Region	Full Fare		Youth/Student Fare		
		Single Ride	Monthly Pass	Single Ride	Monthly Pass	Restrictions
CTA	Chicago, IL	Bus: $2.25 Rail: $2.50	$105	Bus and rail: $0.75	N/A	Weekdays 5:30 AM – 8:30 PM
Metro	Los Angeles, CA	$1.75	$100	$1; Free on DASH buses	$24	K-12 students (under 21 y/o)
MBTA	Boston, MA	Bus: $1.79 Rail: $2.40	$90	Bus: $0.85 Rail: $1.10	$30	Requires school partnership
Metro	Washington, D.C.	Bus: $2.00 Rail: $2-6	Varies	Free	N/A	Only for school-related trips
SEPTA	Philadelphia, PA	Day pass: $9	$96	Day pass: $3.84	N/A	Requires school partnership
NJ Transit	Newark, NJ	Varies	Varies	33% off bus 25% off rail	25% off	K-12 students
Muni and BART	San Francisco, CA	$2.50	$81	$1.25	$40	Youth 5-18 y/o
King County Metro	Seattle, WA	$2.75	N/A	$1.50; Free for HS students	N/A	Discounted for youth 6-18 y/o; Free for HS students
TriMet	Portland, OR	$2.50	$100	$1.75; Free for HS students	$28	Half-price for youth 7-17 y/o; Free for HS students
AC Transit	Oakland, CA	$2.50	$1.25	$84.60	$34	

CHAPTER 4: MODELING APPROACH

To estimate the impact that a discounted youth fare might have on youth transit ridership in the Atlanta region, it was first necessary to develop and refine a model of youth mode choice. The model developed for this research was based on the mode choice components of the Atlanta Regional Commission's activity-based model, the main travel demand model for the region, and includes socioeconomic characteristics of the individual travelers as well as descriptive variables of their journeys. The final model uses a multinomial logit structure to model the choice between driving alone, traveling in a shared personal vehicle, using a non-motorized mode, such as biking or walking, and taking public transit. The sections below provide background on multinomial logit models in general and their previous use in estimating youth mode choice, followed by a description of the data and model used in this research.

4.1 Multinomial Logit Model Background

Multinomial logit (MNL) models are a form of econometric models used to estimate the choice among a set of discrete alternatives (McFadden 1973). They are based on random utility theory, which assumes that the utility of any given alternative consists of some observed portion and some unobserved, or random, portion and that an individual will always choose the alternative that maximizes their utility, even if part of that utility cannot be observed or measured (McFadden 2000). The use of the multinomial logit form to model travel mode choice was introduced by Daniel McFadden in the 1970s and has since become one of the most common methods used in travel demand models (McFadden 1973; 1977; 2000). The name "multinomial logit" comes from the fact that these models compare *multiple nominal*, or categorical, alternatives and assume that the difference between the unobserved utilities of any two alternatives follows the *logistic* distribution. The probability of choosing each discrete alternative is based on the utility of that alternative relative to the utility of all other alternatives in the choice set. That is, only differences in utility across alternatives impact the probability of each alternative. This probability is given by the following equation, where *i* represents the alternative in question, *j* represents each alternative in the choice set, *v* represents observed portion of utility, and *n* represents each individual traveler.

$$P_n(i) = \frac{e^{v_{in}}}{\Sigma_j e^{v_{jn}}} \tag{1}$$

The utilities of each alternative are assumed to be a linear combination of explanatory variables, each of which describes some characteristic of the decision-maker or the alternative itself. In mode choice modeling, the explanatory variables in the utility function of a travel mode often include socioeconomic characteristics of the traveler, such as income and gender, which are usually obtained through a travel diary or survey; descriptions of the traveler's household, such as the number of people or number of vehicles; and factors involved in the journey, such as travel time, distance, and cost. MNL mode choice models thus allow us to assess the factors that make each mode more or less appealing by estimating the observed utility function of each mode, which then gives us insight into how the probability of choosing each mode might be affected by altering one of these factors. On the aggregate level, we can then draw conclusions about the effect that different policies, including transit fare policies, might have on overall mode shares.

4.2 Previous Models of Youth Mode Choice

Though the literature on using multinomial logit models to estimate mode choice of populations in general is much more expansive, there have still been a number of studies that specifically analyzed the mode choices and travel behaviors of children and youth, many of which did so using multinomial logit models. For example, Ewing, Schroeer, and Greene (2004) used data from a travel diary survey conducted by the Florida Department of Transportation in 2000 and a similar survey conducted by the Gainesville Metropolitan Transportation Planning Organization in 2001 to develop a multinomial logit model of students' mode choice for the trip to school. The model included individual choice sets, where walk and bike trips were required to be under 60 minutes to be considered available to a student, rather than assuming all alternatives were available for every trip (Ewing, Schroeer, and Greene 2004). Similarly, both McDonald (2005) and Sener, Lee, and Sidharthan (2019) developed multinomial logit models of the school trip mode choice to identify factors that might make students more likely to walk or bike to school. Internationally, Müller, Tscharaktschiew, and Haase (2008) and Mitra and Buliung (2015) modeled school trips in Germany and Canada, respectively. A common finding among all of these studies was the importance of spatial planning in encouraging children's active travel, as students with shorter walking and biking times and distances were significantly more likely to choose one of these modes (Ewing, Schroeer, and Greene 2004; McDonald 2005a; Sener, Lee, and Sidharthan 2019; Müller, Tscharaktschiew, and Haase 2008; Mitra and Buliung 2015). Overall, researchers who have modeled youth mode choices have tended to focus on factors that might encourage walking and biking; relatively little attention has been given to understanding children's and teens' decisions regarding public transit.

4.3 Data Sources and Collection

The following sections describe each of the data sources that were used to ultimately estimate a multinomial logit mode choice model. The main source of data for this research was the 2011 Regional Household Travel Survey conducted by the Atlanta Regional Commission (Atlanta Regional Commission 2011). However, this data only included information on the modes that the individuals chose; that is, if the individual chose to make a trip by car, the survey data does not contain any information on what the same trip would look like when taken on foot or by transit. Because it is necessary to have data on all available modes for each trip to compare their utilities within the model, additional data sources were used to collect the missing information.

4.3.1. ARC 2011 Regional Household Travel Survey

The ARC Regional Household Travel Survey includes four sets of data: one containing information on the household level, one with individual characteristics, one with information on the places to which each individual traveled during their travel diary day, and a final set containing information on vehicles and the households to which they belong. These datasets are publicly available on ARC's website (Atlanta Regional Commission 2011).

To prepare this data for use in the model, it was necessary to join the information from the separate tables and extract only the trips of interest for this research: those made by individuals 18 years old or younger. First, the person and household datasets were joined to the trip data to assess the relationship between the travelers' personal and household characteristics and their travel behavior. This original trip file had 119,488 trips. However, it was then necessary to create a subset containing only the trips of interest. First, trips made by individuals older than 18 were filtered out of the dataset, leaving 26,105 trips. Over 6,000 of these trips did not have their mode specified; in many cases, this was because the data considered staying home an activity even though no travel, and thus no mode choice, is necessary. Fewer than 10 youth trips were made via taxi or motorcycle, so these trips were also excluded, as it would be impossible to accurately estimate a utility function for these modes with so few trips. After these were excluded, 19,826 trips, made by 5,621 unique individuals, remained.

One source of inaccuracy in the model is the lack of specific coordinates for each trip's origin and destination. Instead, the data included only the numbers of the traffic analysis zones (TAZ) in which each trip began and ended. These numbers correspond to the 2000 Model Traffic Analysis Zone system, which comprises 2,024 zones (Atlanta Regional Commission 2000). With this information, each trip was geocoded to the centroid coordinates of its origin and destination TAZs, regardless of where it actually began and ended within the zones. This simplification also meant that it was impossible to accurately model trips made entirely within one zone, as their origin and destination were assumed to be the same location. These intrazonal trips were eliminated, along with any cases with origin or destination TAZs outside the study zone. The final subset of data contained information on 15,910 one-way trips.

4.3.2. Google Maps Distance Matrix API

The Google Maps Distance Matrix API was used to estimate travel times by car, biking, and walking for all trips (Google Developers n.d.). This tool uses the same

Google Maps functionality that users of their smartphone application or website are familiar with but allows for the quick processing of a large number of queries. As described above, the travel times for each trip were computed from the centroid of its origin TAZ to the centroid of its destination TAZ. This causes some inaccuracy in the estimates, as a trip might actually begin or end closer to the centroid of a neighboring TAZ or might require more or less travel time to reach the assumed route. However, given the lack of exact origin and destination coordinates in the data, this was a necessary simplification.

The Distance Matrix API allows the user to specify a departure time and date in the same way that one might when using the Google Maps smartphone application. The tool also requires that this time be the current time or in the future, a constraint that is likely not noticed by real-time travelers but can create a limitation when the API is used to analyze past trips. In this case, the travel diaries for ARC Regional Household Travel Survey were completed between March 8, 2011 and May 27, 2011, so the true departure times and dates for these trips could not be used in the Distance Matrix API. To address this issue, all trips were recoded to a future date during the week of April 11-17, 2021, which approximates the time of year of the original trips and does not contain any holidays. The days of the week were kept consistent with the original survey data to most accurately account for differences in travel patterns and congestion throughout the week. The resulting time estimates for travel by car, biking, and walking were then added to the existing dataset.

4.3.3. OpenTripPlanner

Although the Google Maps API includes the functionality to estimate travel times on public transit, the limited transit routes and schedules at the time of this research due to COVID-19 led to inaccuracies and missing travel time estimates (Google Developers n.d.). To estimate travel times and identify routes on public transit, the Google Maps API relies on the general transit feed specification (GTFS) of each agency (Google Developers 2020). GTFS is a set of data files, formatted in a consistent way, in which each transit agency publishes their schedule, specifying days of the week, routes, trips, and stop times (Google Developers 2020). When a departure date is put into the Google Maps API, it is matched to the schedule corresponding to its day of the week in the current GTFS, regardless of how far the departure date is in the future. When this research was conducted, many transit agencies, including MARTA, were running limited schedules and routes due to the COVID-19 pandemic. Because of these service limitations, the Google Maps API failed to identify transit trips that were possible at the time of the ARC Regional Household Travel Survey and will likely be possible again following the pandemic.

To more accurately assess which trips in the data are possible via public transit and estimate the time that these trips would take, it was necessary to use another tool called OpenTripPlanner, which allows for the use of historical GTFS rather than limiting analysis to only the current available service (*OpenTripPlanner* (version 1.0) 2016). This research used MARTA GTFS from April 2019, which was before any restrictions were implemented and approximates the time of year of the original survey data. To pull transit directions, trips were recoded with a date between April 21-27, 2019, again keeping days of the week consistent with the original day of the travel diary. The resulting directions included in-vehicle travel times, as well as the time required to walk to the bus stop or transit station and any transfer time required for the journey.

One adjustment was made to the OpenTripPlanner output regarding the assumed initial wait time. The OpenTripPlanner routing assumed that travelers would arrive at the transit station or bus stop at exactly the right time to board the vehicle. However, this is often not the case in reality, as travelers will either arrive randomly or may plan to arrive a little earlier than the scheduled departure time to ensure they don't miss their bus or train. The Transit Capacity and Quality of Service Manual states that for high-frequency service, with headways less than 15 minutes, passengers are most likely to arrive randomly rather than planning their arrival around the service schedule (National Academies of Science, Engineering, and Medicine 2013). However, for low-frequency service, such as MARTA's, passengers are more likely to plan their arrival at the station or stop based on the transit schedule to minimize both their wait time and their chance of arriving after the vehicle has departed (National Academies of Science, Engineering, and Medicine 2013). For the purposes of this research, this initial wait time, which is one component of the total out-of-vehicle travel time for each transit trip, was assumed to be two minutes.

4.3.4. U.S. Department of Energy and Environmental Protection Agency

The operating costs for trips made by automobile consisted only of the estimated fuel cost, as the number of trips in the data that reported paying for tolls and parking was negligible. To estimate the fuel cost for each trip, it was first necessary to identify or approximate the fuel economy for all vehicles in the ARC Regional Household Travel

Survey data. The U.S. Department of Energy and the Environmental Protection Agency maintain a database of fuel economy values for almost every vehicle make and model available in the United States since 1984 (U.S. Department of Energy and U.S. Environmental Protection Agency 2020). For each make, model, and year, the data contains a value for the vehicle's city and highway mileage per gallon of fuel, as well as an overall fuel economy value. However, many of the vehicle names in this data did not match exactly with the vehicle names reported in the survey data, due to differences in capitalization or specific versions of vehicle models, making it difficult to join the fuel economy data to the vehicles in the survey. To simplify the process of joining the two datasets, the vehicles were grouped by class (including station wagon, pickup, sport utility vehicles, two-seat vehicles, and sedans), fuel type (including gas, diesel, flex fuel, electric, and hybrid), and year. The average fuel economy value was then calculated for each of these groups and assigned to vehicles in that category in the survey data. This classification system simplified the process of joining the fuel economy reference data to the vehicle survey data without sacrificing too much accuracy when estimating operating costs.

4.4 Model Development

The models developed and used for this research were based on the mode choice components of the ARC activity-based model. However, due to both constraints on available data and the level of complexity involved in the ARC sub-models, the models used in this analysis were modified and simplified. The sections below describe the ARC mode choice models and the process of estimating the model that was then used to evaluate the impact of different youth fare policies.

4.4.1. ARC Mode Choice Models

The ARC activity-based model has two mode choice components that are most likely to be relevant to youth travel: the School and University Tour Mode Choice Model and the Non-Mandatory Tour and At-Work Subtour Model (WSP/Parsons Brinckerhoff 2017). The School and University Tour Mode Choice Model models the choice between driving alone, taking a shared ride, walking to transit, taking the school bus, and walking or biking as the primary travel mode on a tour to school. It is important to note that this model is estimated on a *tour* rather than *trip* basis. That is, a sequence of trips is grouped into a tour before estimating the mode choice, with specific correspondence rules for the alternatives that are available for each trip within a tour, given the primary tour mode (WSP/Parsons Brinckerhoff 2017). The Non-Mandatory Tour Model is similar but includes the option to drive to transit and excludes the school bus alternative. Both of these models include variables such as travel time and cost on each mode, the individual's income, gender, and age, and characteristics of the tour, such as the number of stops within the tour and the purpose of those stops. They also include characteristics of the built environment, including the percent of roads in the origin and destination TAZs with sidewalks (WSP/Parsons Brinckerhoff 2017). Both of these mode choice models make use of a nested structure, as shown in Figure 1, where similar alternatives are grouped within a nest (WSP/Parsons Brinckerhoff 2017).

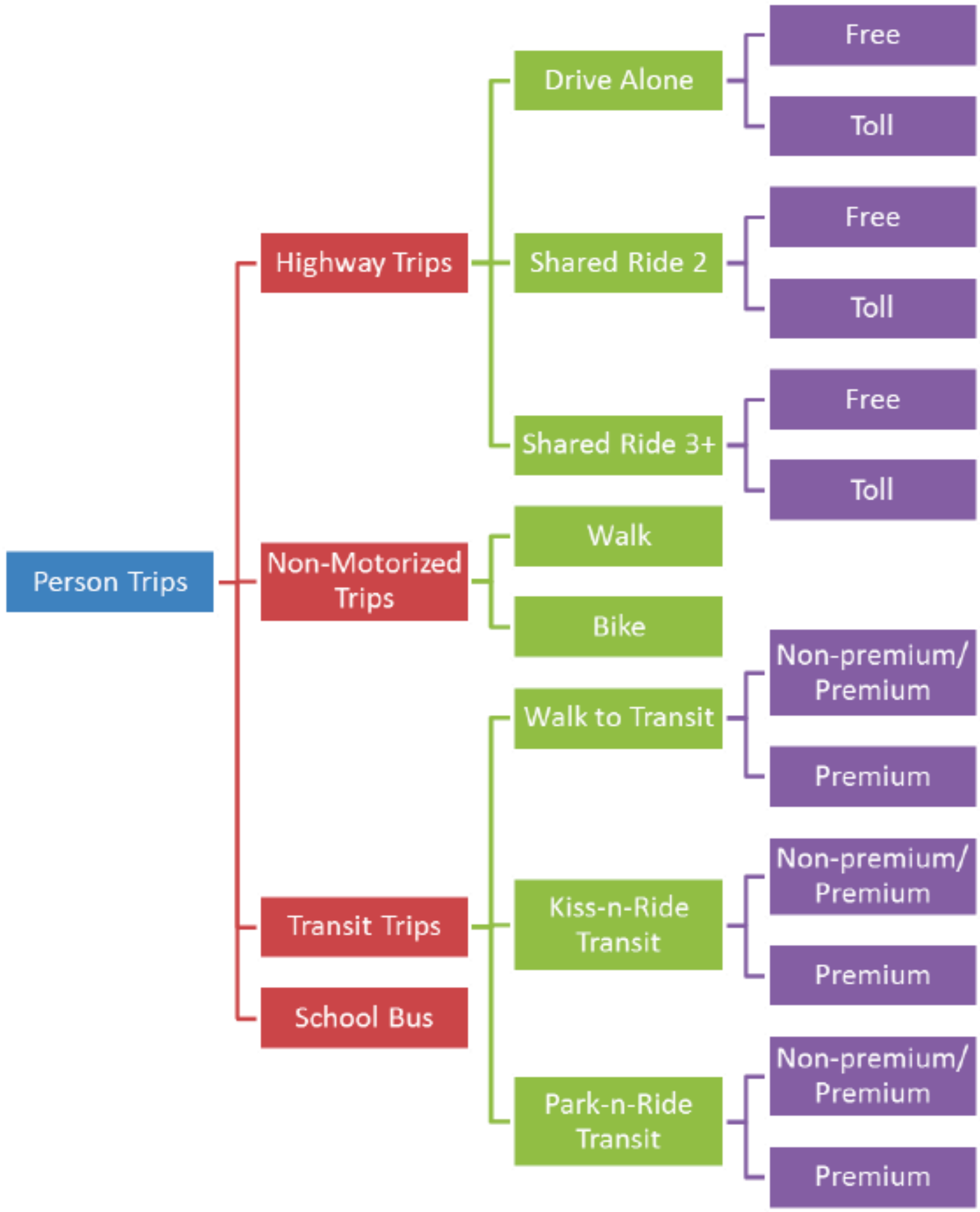

Figure 1: *Nesting structure of the ARC tour mode choice models (WSP/Parsons Brinckerhoff 2017)*

4.4.2. Modifications to ARC Modeling Approach

As mentioned above, it was necessary to simplify the mode choice models used in the ARC activity-based model, as these models included data that was not available for use in this research and involved a level of complexity that was unnecessary for the current evaluation. The two variables that were included in the ARC models but excluded from consideration for this research were the toll costs and the percentage of roads with sidewalks in the origin and destination TAZs of each trip. Only 22 of the 15,910 trips in the data subset of interest reported using a toll lane, and information on the exact toll cost for these trips was unavailable. Though it would be possible to estimate the toll costs for these trips and any other trips with common origins and destinations, many assumptions would be required, and the cost estimates would likely be inaccurate. Because this affected such a small portion of the dataset, it was decided instead to exclude the toll cost variable from the model developed for this research. Similarly, data on the availability of sidewalks in each TAZ is not easily available. Estimating the percentage of streets with a sidewalk available would have required either broad assumptions or a detailed and time-consuming data collection using aerial imagery. The former would result in fairly inaccurate assumptions that are unlikely to be significant in a mode choice model while the latter required more time than was available for this research. For these reasons, it was also decided to exclude the variable representing the availability of sidewalks in each TAZ from the mode choice model.

Another key simplification made when developing the model for this research was the decision to estimate mode choice on a trip, rather than tour, level. Tour-based modeling does allow for more detailed and possibly more realistic analysis. However, it is also more complex than what was needed for the goals of this research. A trip-based model still allows us to assess the potential for youth transit trips and the influence that fare policy might have on youth mode choice.

Finally, the decision was made to only model children's and teens' mode choices for non-school trips, unlike the ARC model, which includes separate mode choice components for school and non-mandatory trips, as described in the previous section. The initial plan for this research did include two separate models for school and non-school trips, following the guidance of the ARC model, as the travel behavior and available alternatives for the trip to school make this a unique mode choice scenario. Similar to commute trips for adults, school trips tend to occur at approximately the same time each weekday and involve a fairly limited number of destinations. Unlike most adults' mode choice when traveling to work, though, most children have the option of a school bus for their journey to school, an alternative that isn't available for any other trip types. As such, it makes sense to model the mode choice for school trips separately from non-school trips. However, the data remaining in the subset of trips of interest did not include enough information to develop a school trip mode choice model that would allow for the evaluation of transit fare policies. A total of 3,842 complete cases in the data were trips taken to school, but not one of these was made on public transit, as shown in Figure 2 below. Because there are no examples of children or teens taking public transit to school in this dataset, it is not possible to estimate the utility function of public transit for this type of trip, unless it is treated as a new mode, as discussed in Chapter 7. Due to the lack of data on school trips via public transit, the analysis and evaluation of potential youth fare policies described in the following sections focused only on non-school trips.

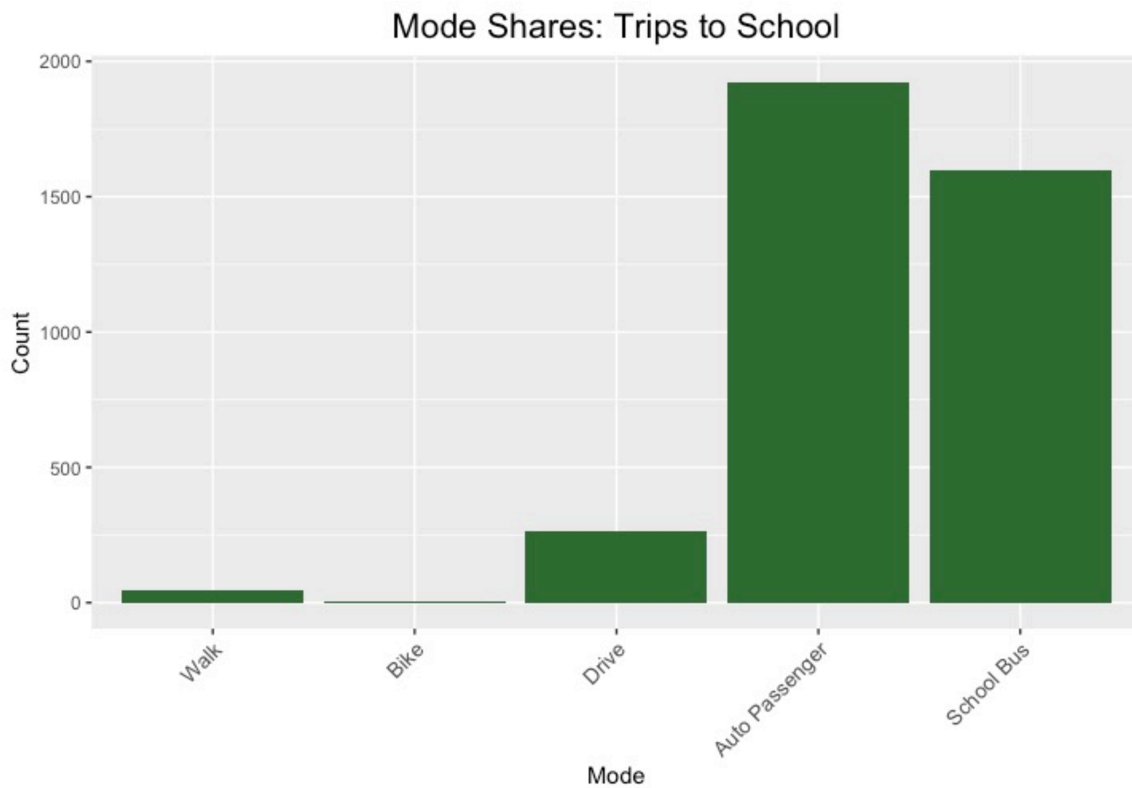

Figure 2: *Mode shares of trips to school (N = 3,842)*

4.4.3. Model Refinement and Final Structure

To develop the model that was used in evaluating different youth fare policies on MARTA, many versions were created and refined before arriving at the final model structure. As described above, this mode choice model was developed based only on trips made by children or youth for a purpose other than "attending class/studying" or "all other activities at school" (Atlanta Regional Commission 2011). This subset included 12,068 trips with complete data, 1,813 of which were made on school buses. Due to the difficulty of estimating school bus availability for each trip, especially because the trips had destinations other than schools, all trips made on school buses were excluded from the analysis, leaving a total of 10,255 non-school trips that were used to estimate the multinomial logit mode choice model.

The models of non-school trip mode choice were estimated using the Apollo package in R (Hess and Palma 2019a; 2019b). This package allows the user to specify the utility functions of each alternative in their model, as well as the overall structure of the discrete choice model, including any nested alternatives. The functions within the Apollo package then use maximum likelihood estimation to estimate the coefficients of each parameter in each utility function (Hess and Palma 2019a; 2019b). Apollo also allows the user to specify a weighting variable, which was used in this case to specify the person weight, a value assigned to each person in the data to align the sample population with the actual population of the Atlanta region (Hess and Palma 2019a; PTV NuStats 2011).

The first set of models estimated the coefficients of each explanatory variable separately. Though a nested structure similar to the one used in the ARC mode choice models was tested, it was determined that the trips made by children and youth in this data did not support the assumptions of the nesting structure, namely that nested alternatives share some portion of their unobserved utilities. Additionally, walk and bike trips were combined into one non-motorized alternative, as only 20 trips within the dataset were taken by bike, making it difficult to accurately estimate a separate utility function for bike trips. This left four discrete alternatives: drive alone, shared auto, non-motorized, and public transit. Although the first set of models was able to represent the utilities of the alternatives with some accuracy, a consistent issue arose when estimating separate coefficients for each parameter: the in-vehicle travel time (IVTT) and cost values for the auto modes, both driving alone and shared, were highly correlated.

Specifically, the correlation coefficient of travel time and operating cost for driving alone was 0.93 and the correlation coefficient of travel time and operating cost for shared auto was 0.85. This high level of correlation between two explanatory variables caused multicollinearity in the model, leading to flawed estimates of the coefficients for these variables.

To address and correct the multicollinearity in the model, common factor analysis was first used to assess the potential to reduce in-vehicle travel time and cost to one "generalized cost score" variable. Common factor analysis produces an output score that is a linear combination of two, or more, input variables, which are standardized then weighted by their influence on the score. In this case, the input variables were the IVTTs and costs for all auto trips, both driving alone and shared. Non-motorized and public transit trips were excluded from the factor analysis, as non-motorized trips in the data have a constant cost of \$0 and public transit trips were also assigned a constant cost of \$2 based on MARTA's fare policy at the time of the survey (Hart 2012). These constant cost values would skew the factor analysis and make it difficult to assess the relationship between IVTT and cost. The resulting scores were initially calculated using the equation below, where w represents the weight, μ represents the mean value of each variable, and σ represents the standard deviation of each variable:

$$Score_i = \left(\frac{w_1(IVTT_i - \mu_{IVTT})}{\sigma_{IVTT}}\right) + \left(\frac{w_2(cost_i - \mu_{cost})}{\sigma_{cost}}\right) \qquad (2)$$

The results of this factor analysis showed that the factor loading values, or weights, were equal for both standardized variables. This meant that the true weighting of IVTT and cost depended mostly on the standard deviation values in the denominator of each term in Equation (2). In this case, computing generalized cost scores for public transit trips would be problematic using Equation (2), as the constant cost values would essentially eliminate cost from the scores when the mean of cost is subtracted from each cost value. However, the output of the factor analysis was still used as a guide in developing a new generalized cost variable, which combined IVTT and operating cost for each mode.

Because the factor analysis showed that the factor loadings depended mostly on the standard deviations of IVTT and cost, the formula for the new generalized cost variable needed to correct for these differing standard deviations while avoiding standardizing the IVTT and cost values, which essentially eliminates the influence of cost from the utilities of the public transit alternative. When the score formula given by Equation (2) is rearranged to place all values over a common denominator, the cost variable is multiplied by the standard deviation of IVTT and vice versa. The standard deviations, rather than their inverses, then become the weights, and the resulting formula for the new generalized cost value is given by Equation (3), where σ again represents the standard deviation of each variable.

$$Generalized\ cost_i = \sigma_{IVTT}(Cost_i) + \sigma_{Cost}(IVTT_i) \tag{3}$$

Using this generalized cost variable, a new set of models was developed until an acceptable iteration was reached. The structure of the utility functions for this final model is shown as follows (individual-specific subscripts are suppressed in the interest of space).

$$V_{drive\ alone} = ASC_{drive} + \beta_1(Generalized\ cost_{drive}) + \beta_2(Worker) + \beta_3(Veh.\ less\ than\ drivers) + \beta_4(High\ income) + \beta_5(Income\ under\ 50K); \quad (4)$$

$$V_{shared\ auto} = ASC_{shared} + \beta_6(Generalized\ cost_{shared}) + \beta_7(Age\ 16\ or\ 17) + \beta_8(Worker) + \beta_9(University\ student) + \beta_{10}(Veh.\ less\ than\ drivers) + \beta_{11}(No\ vehicles) + \beta_{12}(High\ income) + \beta_{13}(Male); \quad (5)$$

$$V_{non-mot.} = ASC_{non-mot} + \beta_{14}(Generalized\ cost_{non-mot}); \text{ and} \quad (6)$$

$$V_{transit} = ASC_{transit} + \beta_{15}(Generalized\ cost_{transit}) + \beta_{16}(OVTT) + \beta_{17}(Worker) + \beta_{18}(University\ student) + \beta_{19}(No\ vehicles) + \beta_{20}(Income\ under\ 20K) + \beta_{21}(Male). \quad (7)$$

As mentioned in Section 4.1, only differences in the utilities across alternatives influence the probability of choosing each alternative. As such, variables that do not differ by alternative can appear in at most *J-1* utility functions, where *J* represents the total number of alternatives. In this case, the non-motorized alternative serves as the base, or reference, mode. Its utility function includes only an alternative-specific constant and the generalized cost for each non-motorized trip but no other variables. The estimated coefficients for the parameters in these functions are shown in Table 2, along with their p-values and diagnostic statistics of the model overall.

***Table 2**: Final mode choice model coefficients (MS = unweighted market share)*

	Coefficient	Variable	Estimate	Std. err.	t-ratio(0)	p-val(0)
Drive alone (MS = 6.24%)	ASC_{drive}	--	0.5641	0.2294	2.4595	0.0139
	β_1	Generalized cost	-0.0014	0.0001	-9.3651	0.0000
	β_2	Worker (1) or not (0)	-0.8357	0.2337	-3.5767	0.0003
	β_3	HH veh.'s < drivers	-1.7973	0.1833	-9.8055	0.0000
	β_4	HH income >100K	0.7644	0.2061	3.7094	0.0002
	β_5	HH income <50K	-0.5049	0.1668	-3.0267	0.0025
Shared auto (MS = 90.76%)	ASC_{shared}	--	1.3641	0.1733	7.8694	0.0000
	β_6	Generalized cost	-0.0019	0.0002	-9.5230	0.0000
	β_7	Age 16 or 17	-0.5210	0.1128	-4.6175	0.0000
	β_8	Worker (1) or not (0)	-1.5607	0.2163	-7.2163	0.0000
	β_9	University student	-0.5352	0.1821	-2.9385	0.0033
	β_{10}	HH veh.'s < drivers	-1.0188	0.1406	-7.2481	0.0000
	β_{11}	No HH vehicles	-3.3783	0.2220	-15.2151	0.0000
	β_{12}	HH income >100K	0.6847	0.1577	4.3414	0.0000
	β_{13}	Male	-0.3739	0.0926	-4.0365	0.0001
Non-motorized (MS = 2.23%)	$ASC_{non-mot}$	--	0.0000	NA	NA	NA
	β_{14}	Generalized cost	-0.0007	0.0000	-18.4668	0.0000
Public transit (MS = 0.77%)	$ASC_{transit}$	--	2.0146	0.4693	4.2931	0.0000
	β_{15}	Total OVTT	-0.1207	0.0137	-8.8023	0.0000
	β_{16}	Generalized cost	-0.0013	0.0002	-8.2625	0.0000
	β_{17}	Worker (1) or not (0)	-1.0219	0.3927	-2.6022	0.0093
	β_{18}	University student	4.1077	0.5852	7.0194	0.0000
	β_{19}	No HH vehicles	1.9596	0.3218	6.0896	0.0000
	β_{20}	HH income <20K	-1.4332	0.3150	-4.5506	0.0000
	β_{21}	Male	-0.7278	0.2543	-2.8623	0.0042

$N = 10{,}255$	Public transit only available for 2,308 cases	
$LL_{EL} = -8560.704$	LL_{MS} = 2564.812	$LL_{final} = -1935.407$
$\rho^2(EL\ Base) = 0.7739$	$\rho^2(MS\ Base) = 0.2454$	

As described above, the generalized cost values used in each utility function account for only IVTT and operating cost. However, the public transit alternative includes out-of-vehicle travel time (OVTT), for which a separate coefficient was estimated. To draw any conclusions about the relative impact of IVTT and OVTT on the utility of the transit alternative, it is necessary to separate the coefficient of IVTT from the generalized cost for public transit before we can compare it with the coefficient of OVTT. The separated IVTT coefficient was computed using the following equation:

$$\beta_{IVTT_{PT}} = \beta_{cost\ score_{PT}}(\alpha_{IVTT}) = \beta_{cost\ score_{PT}}(\sigma_{auto\ cost}) \tag{8}$$

In this data, the standard deviation of auto cost, including both driving alone and shared auto, is 110.05. The resulting IVTT coefficient for public transit is thus $\beta_{IVTT_{PT}} = -0.1484$. The OVTT coefficient for public transit, which is represented by β_{15} in Table 2 and the preceding utility functions, is -0.1207. Though we would expect the coefficient of OVTT to be larger in magnitude, as time spent waiting or walking is generally perceived as a greater burden or as taking longer than time spent riding the bus or train, these coefficient values are close enough to each other to be essentially equal. Based on the literature, the unusual relative values of the IVTT and OVTT coefficients may also reflect the unique characteristics of transit travel by youth. Children and especially teens traveling on public transit may be more likely to travel in groups of friends than are adults and thus may use their journey as a time for socialization (Jones et al. 2012; Goodman et al. 2014; Symes 2007). In the data used in this model, the mean number of people on each trip is 2.91, indicating the tendency to travel in a group. Because these children and teens can talk to their friends just as easily, if not more so, while waiting for the bus or train as while riding in the vehicle, we would expect the social aspect of youth transit travel to have the potential to close the gap in the marginal utilities, or really dis-utilities, of IVTT and OVTT.

CHAPTER 5: ATLANTA CASE STUDY

After the mode choice model was developed, it was used to evaluate potential youth fare policies that MARTA could implement, as described in the following sections. The first section presents an overall description of youth travel behavior and trends noted in the ARC Regional Household Travel Survey data to provide context for the policy evaluations that follow. Eight potential youth fare policies were then tested, including the $2 fare at the time of the travel survey and the current $2.50 fare (Hart 2012; MARTA n.d.). For each policy, the estimated ridership and total revenue for non-school youth trips were calculated based on the model. Each subsection also provides a description of likely MARTA riders, including breakdowns by race and income, to better assess the equity implications of different possible youth fares. The final section of this chapter summarizes the estimated ridership and revenue values for all policies and offers recommendations based on these results.

5.1 Current Youth Travel Patterns in Atlanta

As described in Section 4.3, the original ARC Regional Household Travel Survey data was first filtered to exclude trips made by individuals over 18 years of age, intrazonal trips or trips that began or ended outside of the study area, and trips without their mode specified or with an uncommon mode, leaving 15,910 cases reported in the survey data, which represent approximately 17,840 trips when weighted to align the sample with the overall population. This subset includes both school and non-school trips. Although only non-school trips were used to estimate the model, as explained in

Section 4.4, the statistics and descriptions of youth travel behavior presented in this section include school trips as well.

5.1.1. Independent Mobility Trends

Of great interest in the field of youth travel research, as noted in Chapter 2, is the question of children's and teens' independent mobility, or alternatively, the influence that parents have on their children's travel behavior, and the factors that influence each (Hillman, Adams, and Whitelegg 1990; Carver, Timperio, and Crawford 2013; Fyhri and Hjorthol 2009). Of the youth trips reported in the ARC Regional Household Travel Survey data, 2,866 were made by youth traveling entirely independently. When weighted to match the population, these cases represent approximately 3,325 trips, or 18.6% of the weighted total number of trips. Such trips were made by 1,489 different individuals from 1,209 unique households. The largest portion of trips by far were trips made with at least one household member. The data reported 11,515 cases of this type, which represent approximately 12,901 trips when weighted, accounting for approximately 72.3% of the youth trips studied. They were made by 4,003 different individuals from 2,389 unique households. The smallest portion of youth trips were those that were accompanied by someone outside the individual's household. Unfortunately, the data does not contain information about anyone outside of the survey households, including those who accompanied children and teens on their trips. As such, it is difficult to draw conclusions about the dynamic of these trips; a child traveling with another young friend would appear the same in the data as a child traveling with an adult caretaker. These trips totaled approximately 1,614 when weighted, accounting for about 9.0% of the trips studied, and were made by 927 unique individuals from 777 different households. The weighted and unweighted counts and percentage of each of these trip types are presented in Table 3 below.

Table 3: *Breakdown of independent and accompanied trips*

Trip Type	Number of Cases	Weighted Number of Trips	Percentage
Independent	2,866	3,325	18.64%
Accompanied by HH Member	11,515	12,901	72.31%
Accompanied by Non-HH Member	1,529	1,614	9.05%
Total	15,910	17,840	100%

Figure 3 displays how the proportion of each trip type varies at each age. Unsurprisingly, older children and teens made a larger percentage of their trips independently, with a notable jump at age 16, when many teens receive their driver's licenses. The fraction of trips that were accompanied by someone outside the child's household also grew slightly beginning around age 9, suggesting that at least some of these trips could be made by children who are granted increased independent mobility to travel with friends as they get older. Figure 4, Figure 5, and Figure 6 show the raw count of each trip type separated by age and support this conclusion as well; older children make more independent trips and trips with people outside their household, but fewer trips with household members, than younger children do. Though it is possible that some of the accompanying individuals from outside the household are adults or other caretakers, the fact that older children make more of these trips suggests that they are associated with some level of independent mobility.

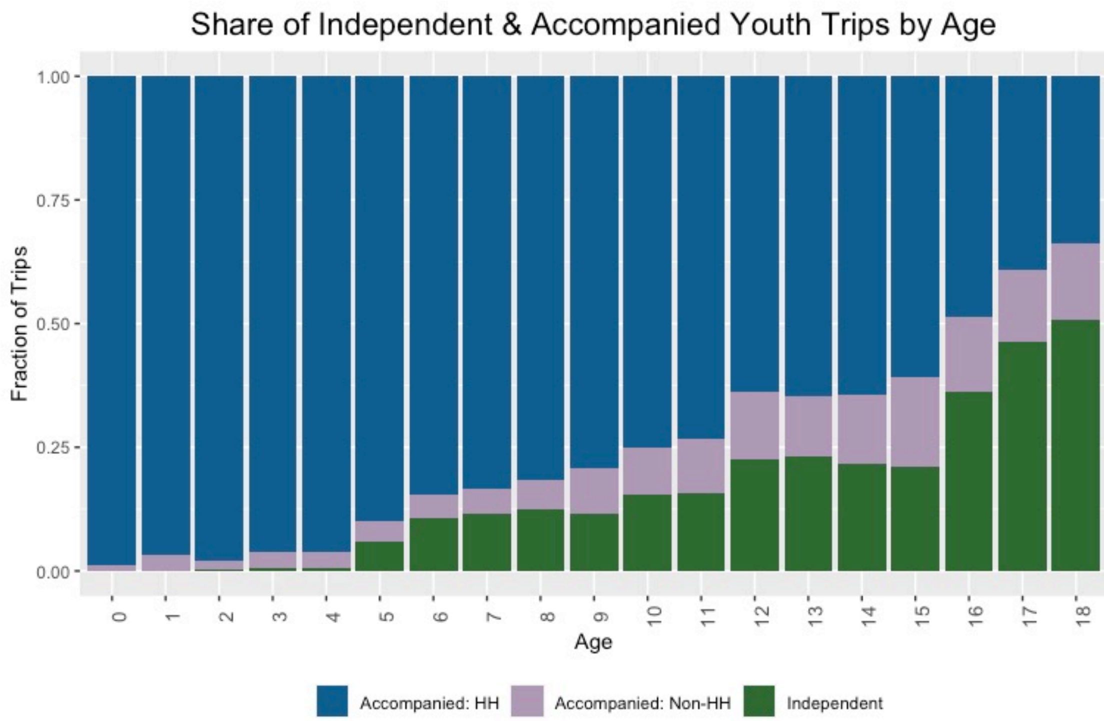

Figure 3: *Proportion of trips that are independent and accompanied at each age (N = 17,840)*

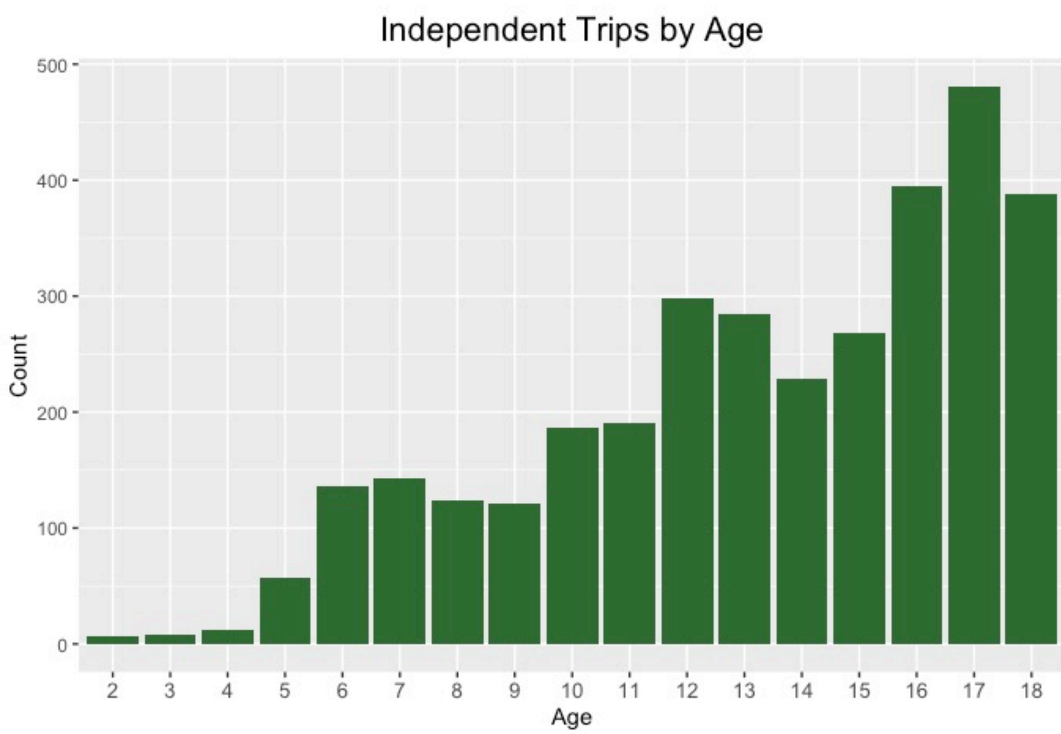

Figure 4: *Weighted number of independent trips made by youth at each age (N = 3,325)*

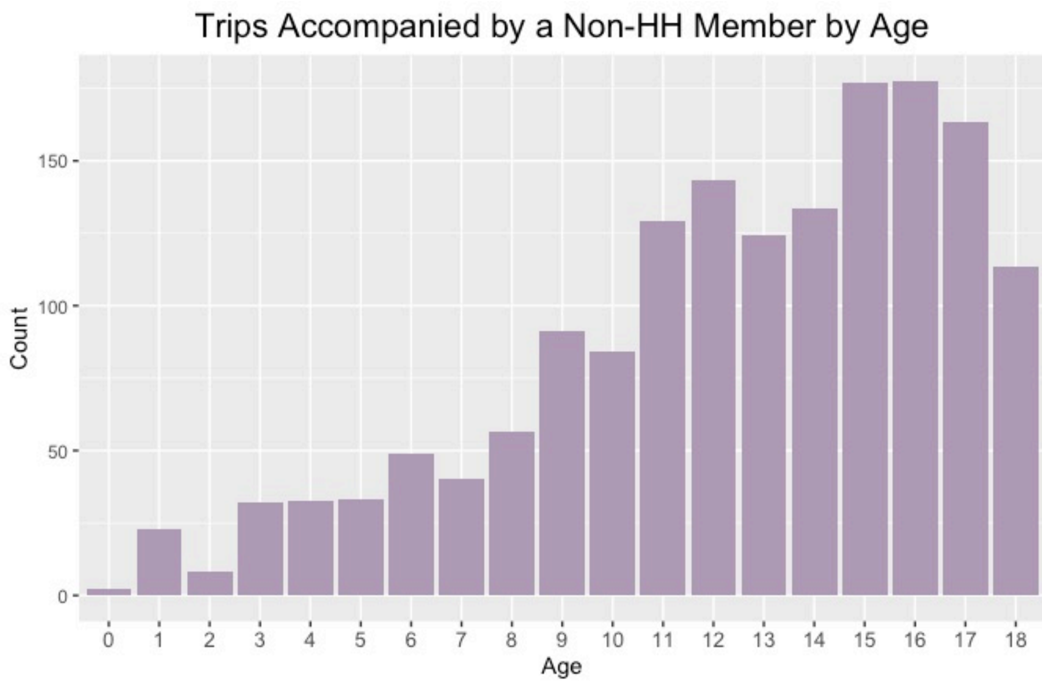

Figure 5: *Weighted number of youth trips accompanied by someone outside HH (N = 1,614)*

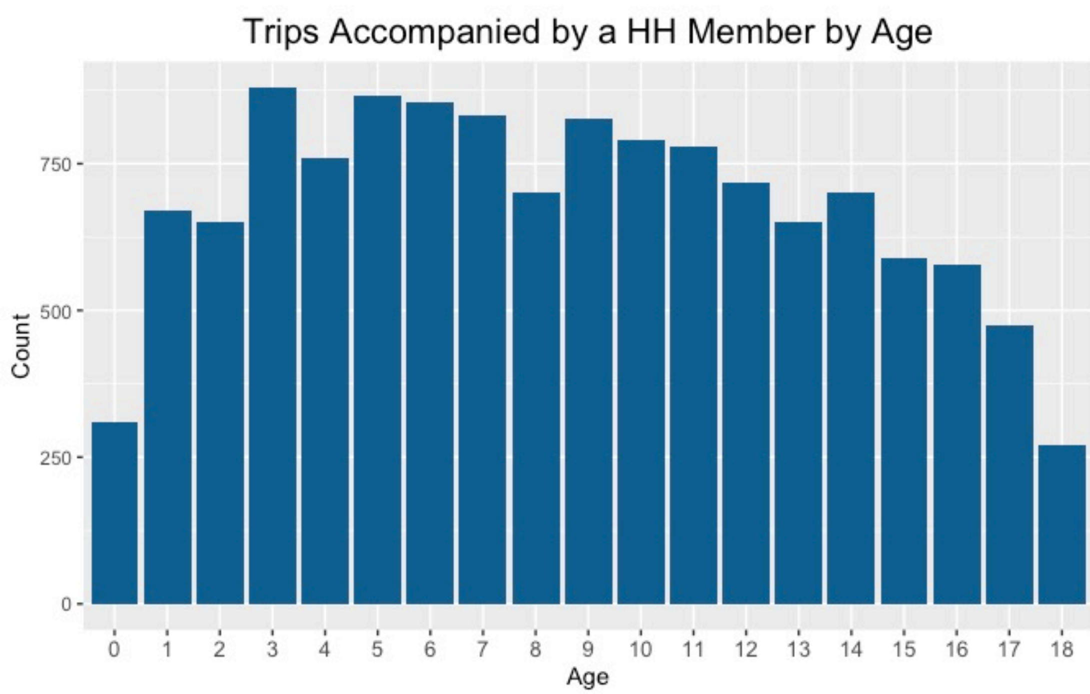

Figure 6: *Weighted number of trips made by youth accompanied by a HH member (N = 12,901)*

5.1.2. Existing Mode Shares

Before testing the different fare policies, the mode shares represented by the survey data were first examined in a more general sense to better understand the relationship between independent mobility and mode choice. Figure 7 shows the weighted count of trips that were independent or accompanied by a household member or non-household member for each mode. By far, the most common trip type and mode combination are trips accompanied by a household member while riding in a private automobile. This result was unsurprising, given the growing prevalence of parental chauffeuring across the United States (McDonald 2005a).

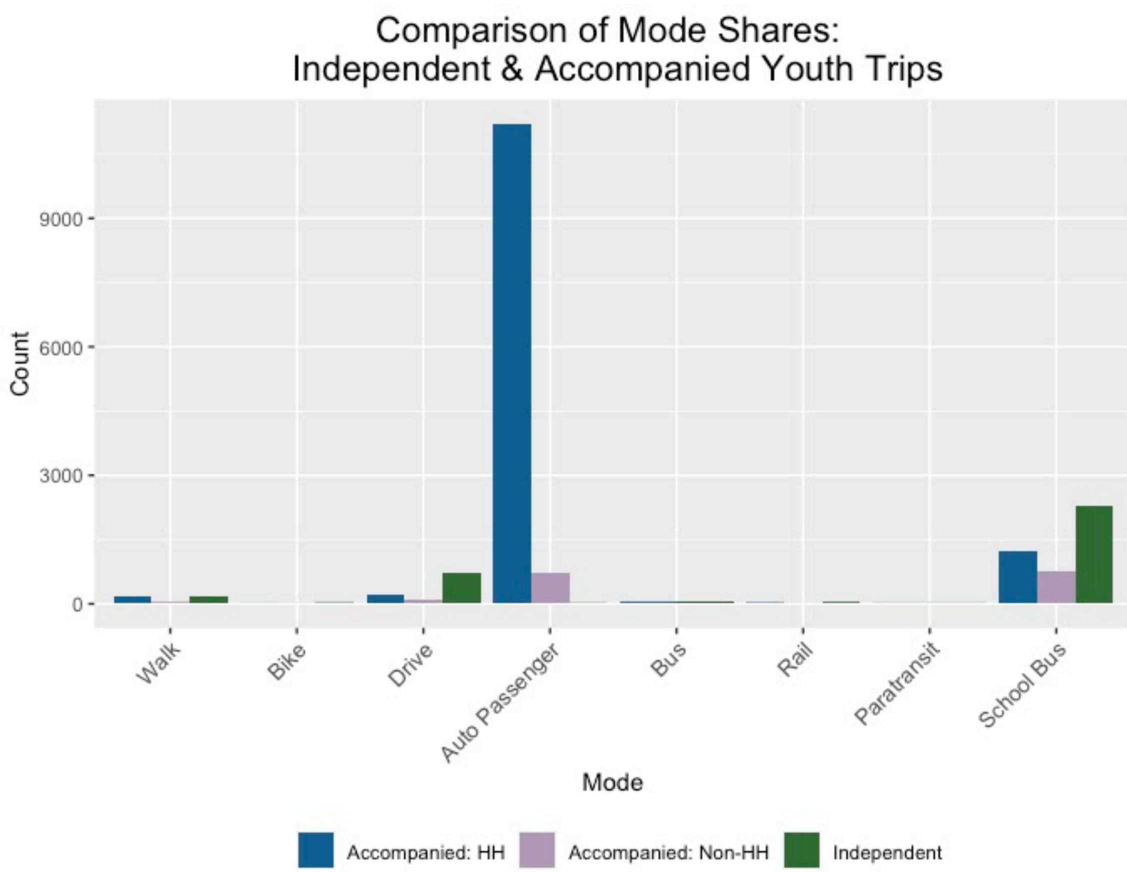

Figure 7: *Weighted number of trips by type and mode (N = 17,840)*

Compared to automobile passenger trips with a household member, the number of trips made via the three public transit modes (bus, rail, and paratransit) are almost impossible to see in Figure 7. Because the focus of this research was youth transit travel, the relatively few transit trips reported in the survey were examined more closely. Figure 8 shows the weighted number of transit trips made by youth of each age. The graph shows that most of the transit trips reported in the survey were made by teenagers 15 and over. The jump in the number of transit trips at age 18 likely represents the influence of university students. Figure 9 shows the mode share of public transit at each age. Looking at the mode shares helps us understand how transit trips compared to all other trips made by youth of each age. For example, Figure 9 shows that the large number of transit trips made by older teens relative to youth of other ages is truly reflective of an increased propensity to use transit at that age and not simply due to an increase in travel overall. This trend, along with those described above, helps provide context for the youth fare policies that are explored in the next sections.

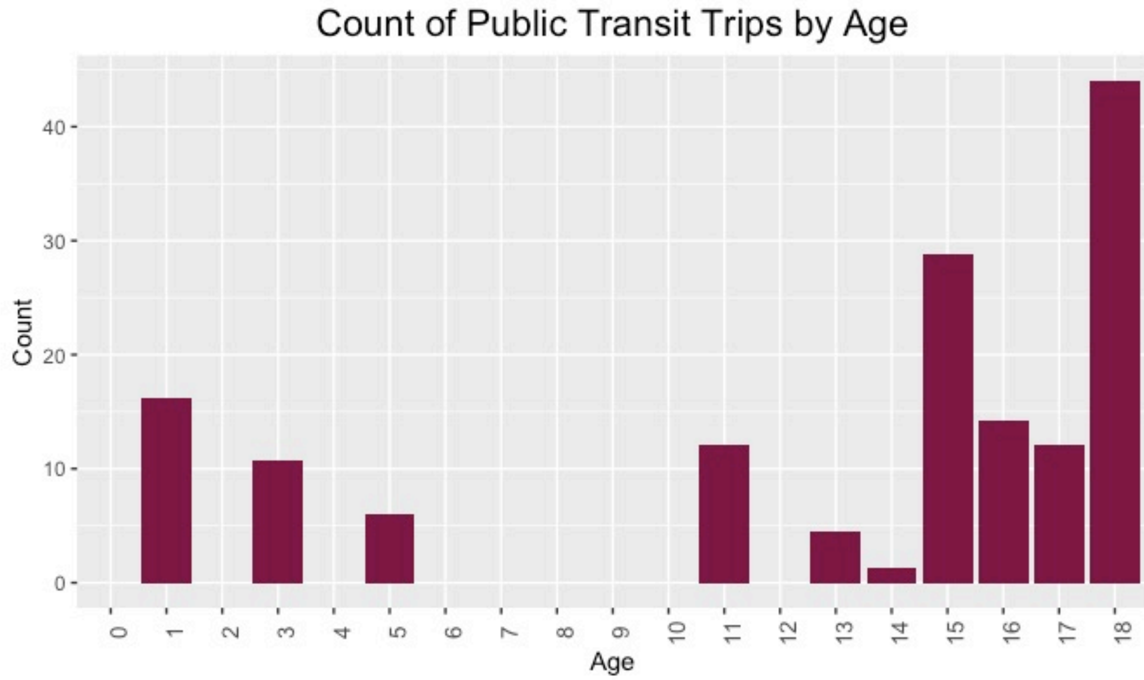

Figure 8: *Weighted count of public transit trips made by youth of each age (N=150)*

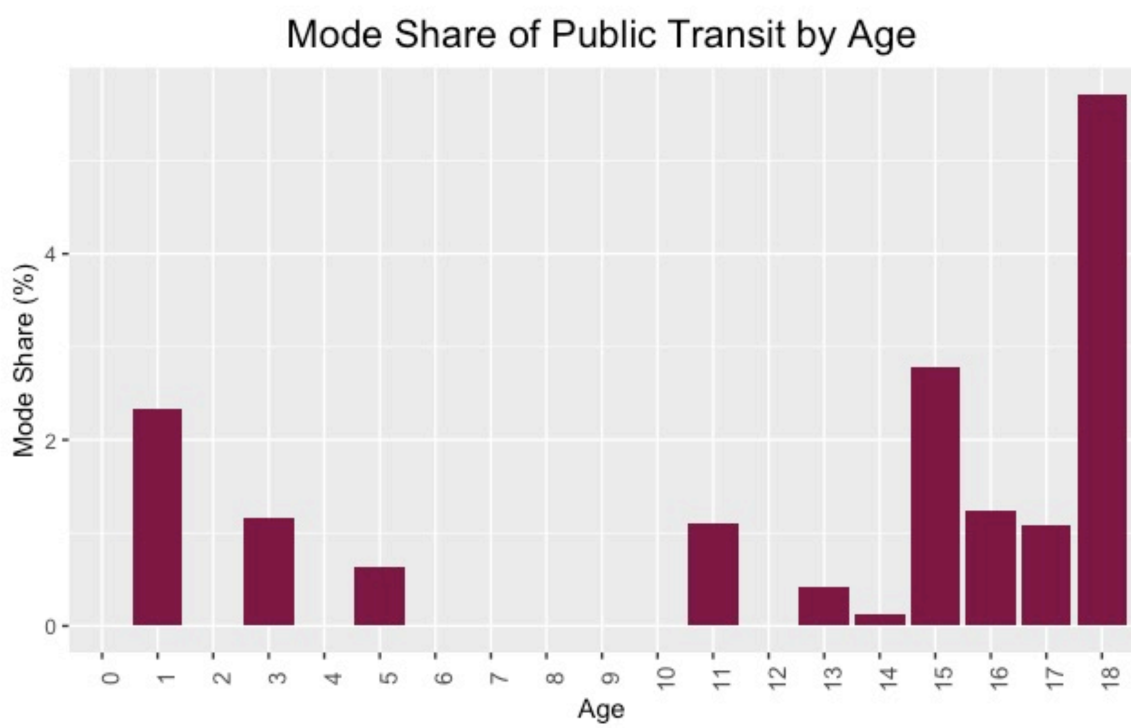

Figure 9: *Mode share of public transit for youth trips by age (N = 150)*

5.2 MARTA Fare Policies: Past and Current

Using the model described in Section 4.4, various youth fare policies were evaluated to estimate their impact on ridership, mode share, and revenue, as well as characteristics of the riders they are likely to attract. When comparing these results, it is important to remember that only non-school trips were included in the model development and subsequent fare policy evaluations. Therefore, it is possible that additional transit trips could be made for the purpose of attending school, but the survey data did not contain any such trips, making it difficult to accurately predict how they might be influenced by fare policy. It is also important to remember that these results are estimates based on a model that is inevitably imperfect, as it is impossible to account for every possible factor that might influence someone's mode choice. Still, the results help us understand and quantify the possible impacts of different fare policies.

The two policies presented in this section are the fare policy that was in place at the time of the ARC Regional Household Travel Survey in 2011 and the current MARTA fare. For each policy, the estimated mode shares were calculated by allocating each alternative's predicted probability for each trip, rather than assigning 100% of each trip to its most likely alternative. This method is more accurate on the aggregate level, as it better accounts for cases where the utilities of alternatives are very similar. For example, if an individual's predicted probability of driving alone is 51%, but their predicted probability of choosing public transit is 47%, simply assigning 100% of this case to driving alone would clearly disregard the still fairly large chance that they choose public transit. This is especially important when we remember that the model only represents the observable portions of utilities. If an individual's observed utilities for two alternatives are very close, it is very possible that the unobserved portion could “tip the scales” and cause the individual to choose the alternative with the slightly lower observed utility. Furthermore, it is useful to remember that the available data constitute only a small sample of the study population, with each trip in the sample effectively representing a large number of statistically similar trips in the overall population of children and teens. From that perspective, the hypothetical drive alone and transit probabilities of 51% and 47%, respectively, can be viewed as meaning that, out of 100 statistically similar trips, about 51 of them (not all 100) would be made by driving alone, while about 47 of them (not 0) would be made by transit.

5.2.1. Fare Policy at the Time of Survey

In 2011, the year in which the ARC Regional Household Travel Survey was conducted, MARTA charged $2 per one-way trip (Hart 2012). This fare was used when developing the original generalized costs of transit trips and estimating the model parameters listed in Section 4.4. Based on these costs and their impact on the utility of public transit relative to other available modes, the model predicts that approximately 76.8 of the 10,255 non-school youth trips examined would be taken on MARTA each day, without accounting for the sample weights. When these weights are applied to better align the characteristics of individuals in the survey sample with the characteristics of the overall population, this ridership estimate increases to approximately 147.1 trips out of a weighted total of 11,278 non-school youth trips, or 1.3% of trips. At $2 per trip, this equates to an estimated farebox revenue of $294.20 per day or $107,384.37 per year derived from non-school youth trips.

Figure 10 and Figure 11 show the breakdown of estimated transit trips by race and income level of the traveler under a $2 fare policy. African Americans are by far the largest racial group among the estimated riders. Almost all income categories are present among the estimated transit riders, but the majority of transit trips are made by riders that come from households making less than $40,000 per year.

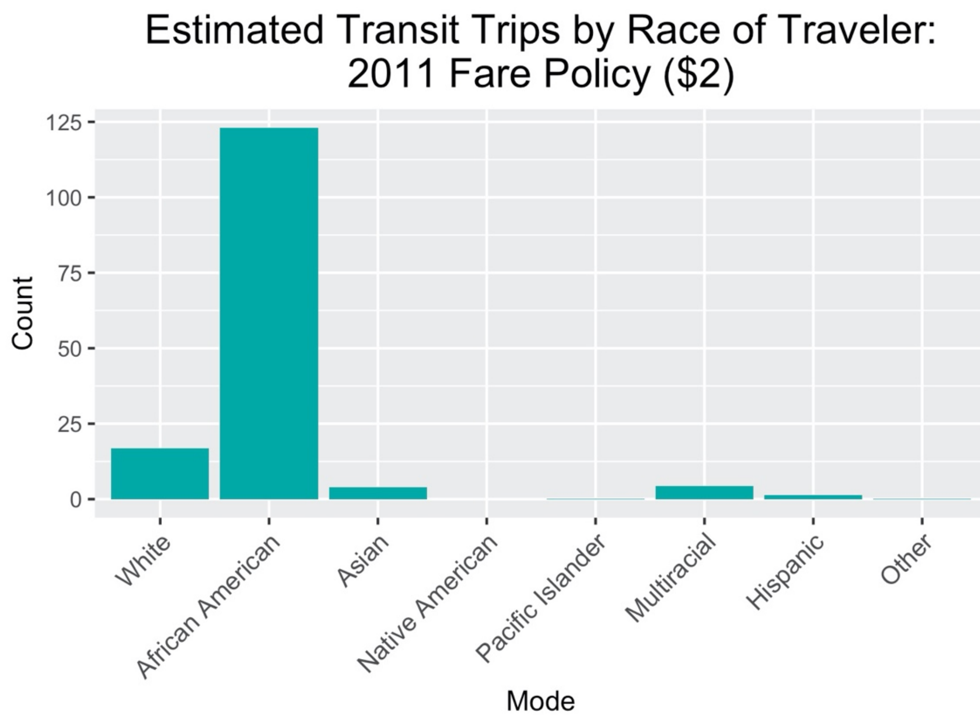

Figure 10: *Estimated transit trips by race of traveler under 2011 fare policy (weighted N=11,278)*

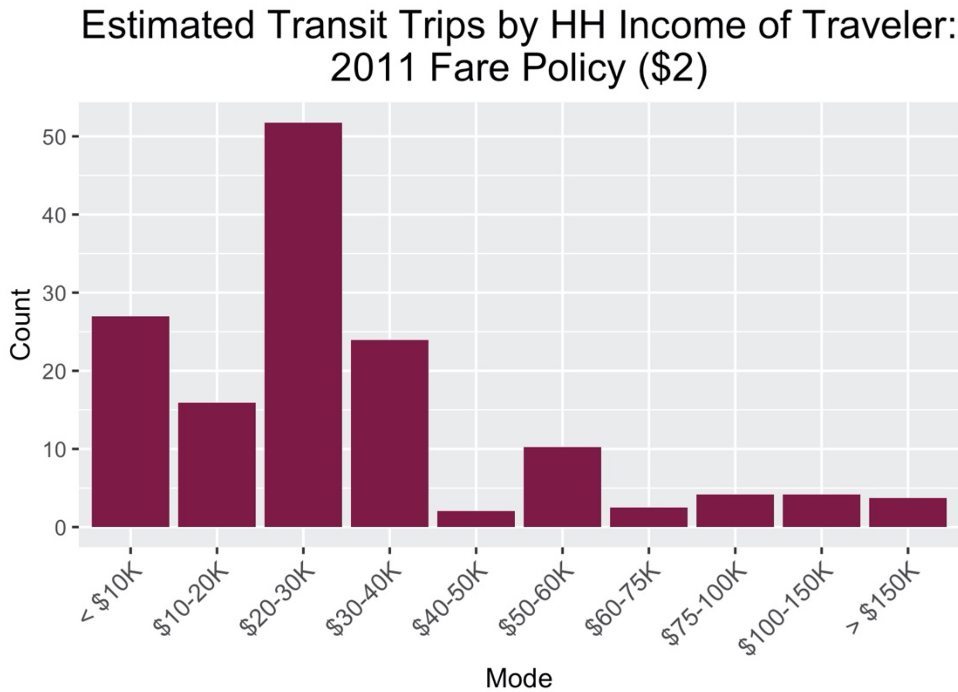

Figure 11: *Estimated transit trips by HH income of traveler under 2011 fare policy (weighted N=11,278)*

5.2.2. Current MARTA Fare Policy

In 2012, MARTA increased the fare for a one-way trip to $2.50 (Hart 2012). Based on the model results, this fare increase was likely to have negatively impacted youth transit ridership. Public transit generalized costs were computed using a fare of $2.50, and the utility of transit was recalculated for each trip and compared to the existing utilities of other modes. Based on these results, the expected number of daily non-school youth transit trips under the current fare policy is approximately 112.8 out of 11,278 total trips, when weighted to match population demographics. This equates to a mode share of 1.0% and is a decrease of about 34 trips from the 2011 fare policy. The expected daily farebox revenue under this policy is $281.91, which translates to an annual farebox revenue of $102,897.03. When examined by race and income, the estimated transit riders under the current fare policy largely resemble the characteristics of riders under the 2011 policy, as shown in Figure 12 and Figure 13.

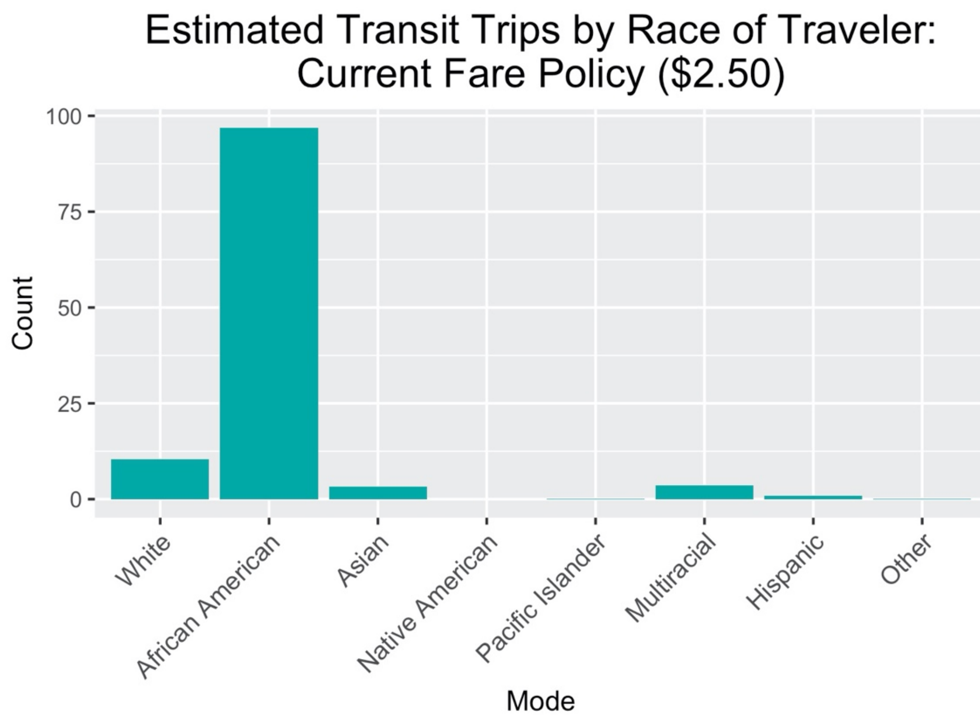

Figure 12: *Estimated transit trips by race of traveler with current fare (weighted N=11,278)*

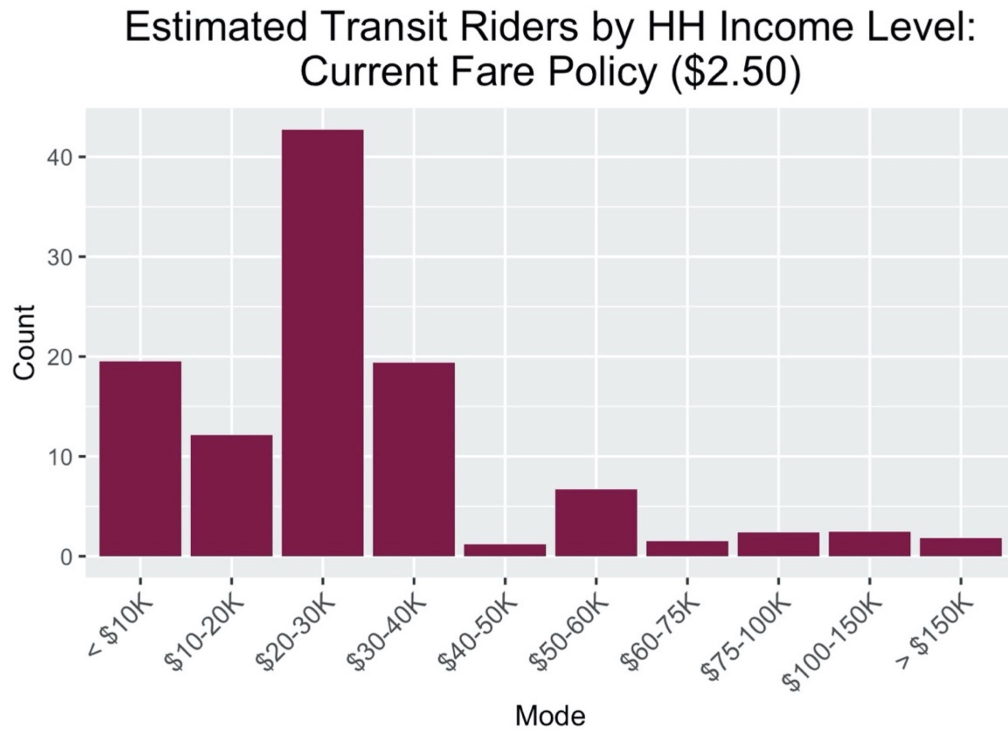

Figure 13: *Estimated transit trips by HH income of traveler with current fare (weighted N=11,278)*

5.3 Evaluating Potential MARTA Youth Fare Policies

After studying the past and current MARTA fare policies and their impacts on ridership and revenue, six potential youth fare policies were evaluated on the same metrics. The following subsections describe each of these policies and their estimated impacts. The first three policies would apply to all youth while the last three would apply to only low-income youth who meet qualifications similar to those required for free or reduced-price lunches at school. The criteria used to determine whether a student qualifies for free or reduced-price lunch are based on a combination of household size and income and are set for each state by the U.S. Department of Agriculture (U.S. Department of Agriculture n.d.). These criteria are often used when assessing school funding needs and students' qualifications for other assistance or benefits. Among the trips included in the model estimation and subsequent fare evaluation, a weighted total of approximately 3,907.4, or 34.6%, were made by youth who meet the criteria for low-income fares.

5.3.1. Discounted Youth Fare: Half-Price

The first new policy tested would offer youth transit passes for $1.25, which is half of the current fare. Based on the model, this policy would result in an estimated 215.2 non-school youth transit trips each day out of the weighted total of 11,278 trips studied. This equates to a mode share of 1.91% and is approximately a 91% increase from the ridership estimated under the current fare policy. At $1.25 per trip, this translates to $268.97 in estimated farebox revenue each day, or $98,173.91 each year. Therefore, though this fare policy is predicted to nearly double youth non-school ridership, the lower fare would result in a slight decrease of about $13 in farebox revenue each day. The socioeconomic characteristics of the youth predicted to make transit trips under this policy, shown in Figure 14 and Figure 15, are similar to those seen under the current policy, but we do observe a slight increase in the share of trips whose riders belong to the lowest income category, from 17.3% of trips under the current policy to 19.0% of trips under a youth fare policy that offers half-priced fares.

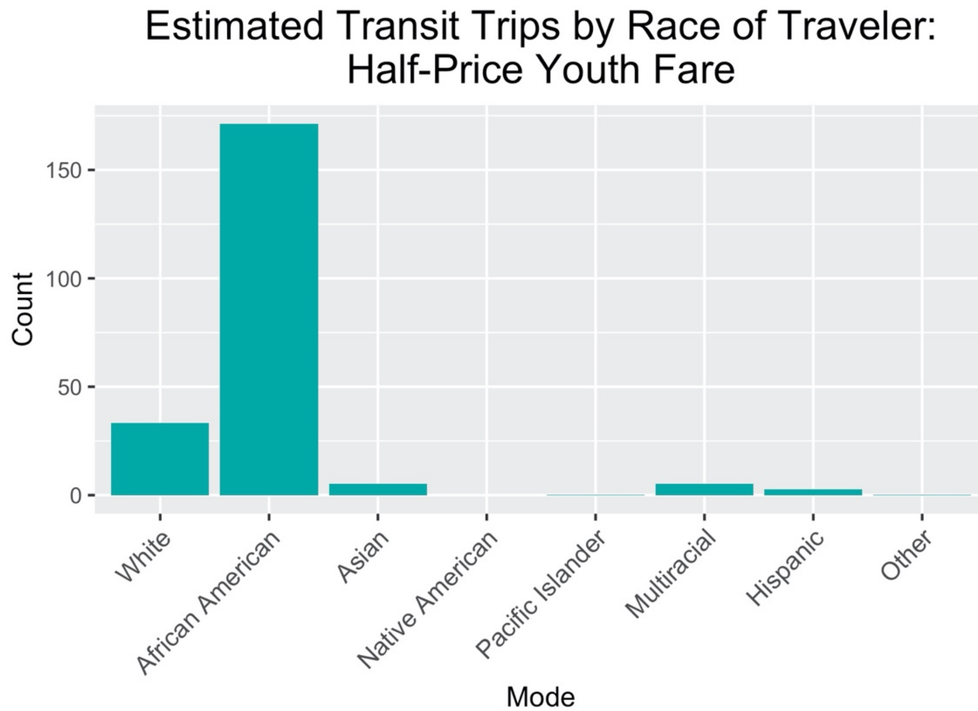

Figure 14: *Estimated transit trips by race of traveler under half-price ($1.25) youth fare (weighted N=11,278)*

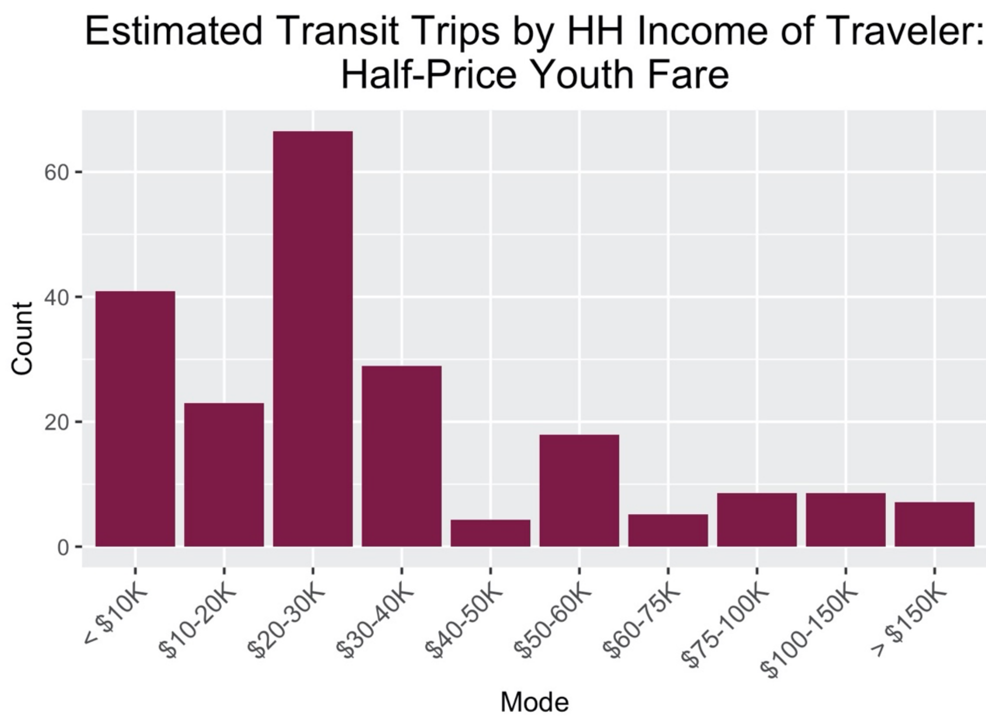

Figure 15: *Estimated transit trips by HH income of traveler under half-price ($1.25) youth fare (weighted N=11,278)*

5.3.2. Discounted Youth Fare: $1

The next hypothetical fare policy tested would further reduce the youth fare on MARTA to only $1 per one-way trip for all children and teens 18 and under. Under this policy, the expected number of daily non-school transit trips is 243.7, a 116% increase over the estimated youth ridership under the current fare policy. This would account for 2.16% of the 11,278 trips examined and result in an estimated $243.72 in daily farebox revenue or $88,957.93 in annual farebox revenue. The socioeconomic characteristics of the youth making the predicted trips are similar to those seen under the half-price fare, as shown in Figure 16, with another slight increase in the share of trips made by riders from the lowest income category.

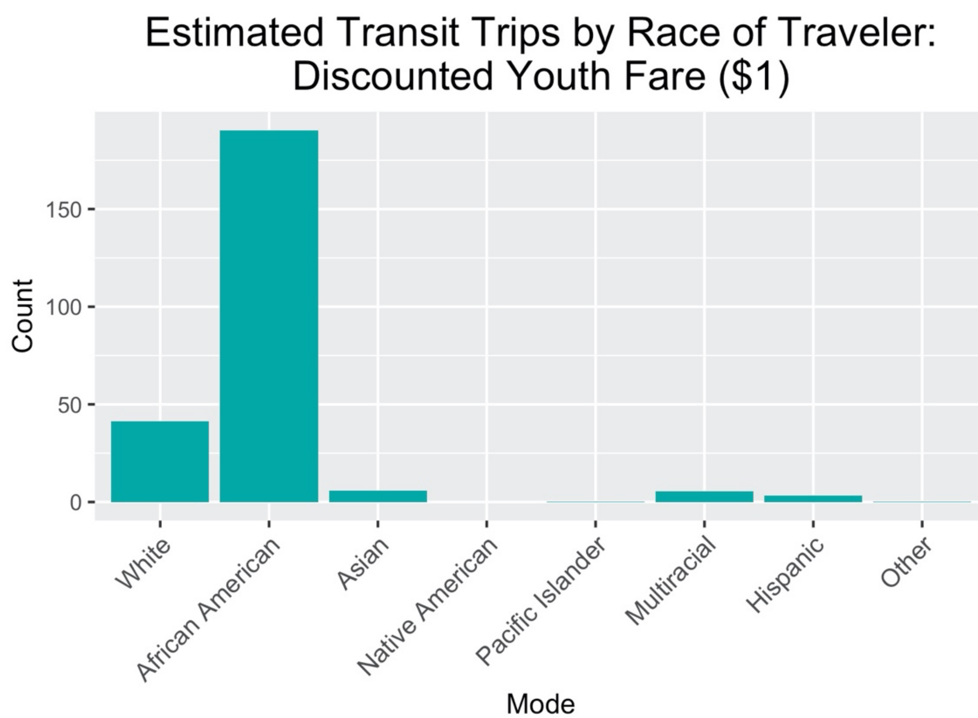

Figure 16: *Estimated transit trips by race of traveler under discounted ($1) youth fare (weighted N=11,278)*

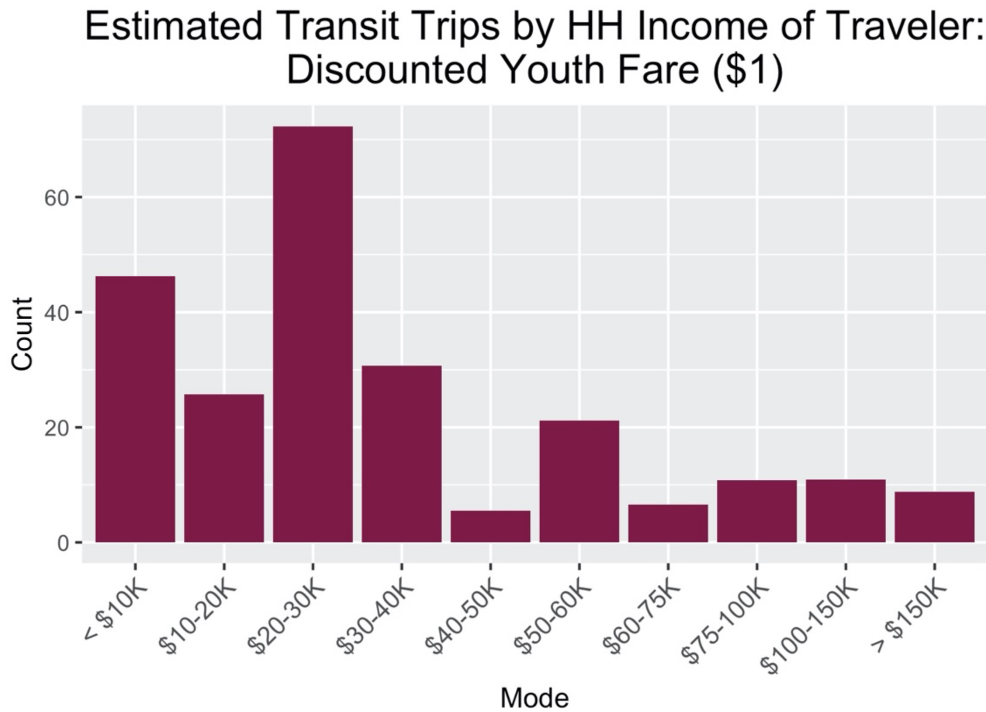

Figure 17: *Estimated transit trips by HH income of traveler under discounted ($1) youth fare (weighted N=11,278)*

5.3.3. Free Youth Fare

Unsurprisingly, the fare policy that is predicted to result in the largest ridership is one that offers free transit access to all youth. Under this policy, estimated daily ridership for non-school trips is approximately 398.8, over 3.5 times the estimated ridership under the current fare. This would account for 3.54% of all trips. Of course, though the estimated ridership would be highest under a free fare, the farebox revenue from youth trips would be $0. The free fare is also expected to attract more riders across racial groups and income levels, as shown in Figure 18, with some of the largest increases surprisingly seen in the higher income levels.

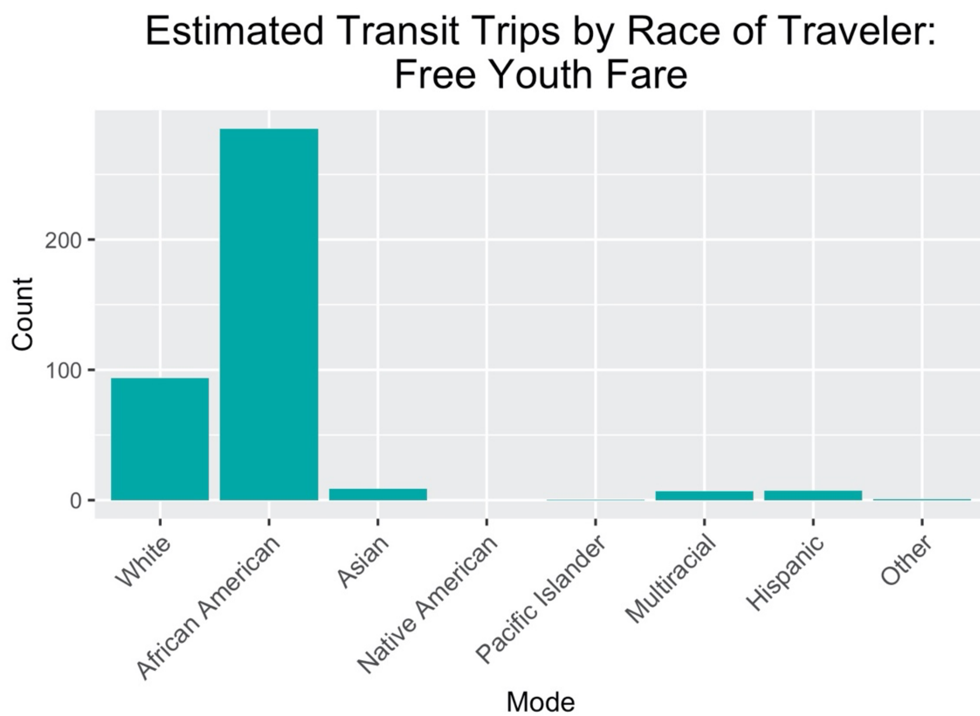

Figure 18: *Estimated transit trips by race of traveler under free youth fare policy (weighted N=11,278)*

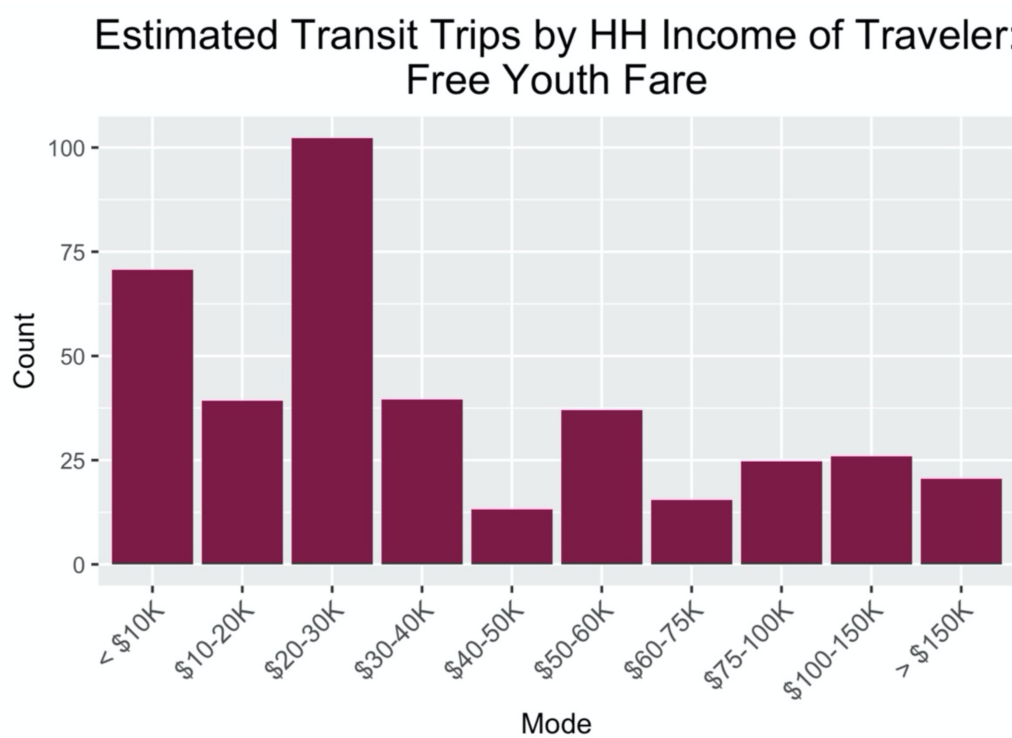

Figure 19: *Estimated transit trips by HH income of traveler under free youth fare policy (weighted N=11,278)*

5.3.4. Discounted Fare for Low-Income Youth: Half-Price

The first of three fare policies tested that would apply to only low-income youth was one that would offer half-price ($1.25) fare to students who meet qualifications similar to those required for free and reduced-price lunch but require all other youth to pay the current regular fare of $2.50. The goal of such a policy would be to make transit more financially feasible for low-income youth while asking youth who are more likely to be able to afford it to pay the full fare. Under this policy, the estimated number of daily non-school trips is 177.3, when weighted to match population demographics, which is higher than estimated ridership under the current policy but unsurprisingly lower than under a policy that offers discounts to all youth. This translates to a mode share of 1.57% and estimated farebox revenue of $257.23 per day or $93,889.60 per year. It does not appear that this policy would influence the racial makeup of the youth making the estimated transit trips compared to those under the current policy, as shown in Figure 20, but it does seem to have the intended effect of attracting more low-income riders, as shown in Figure 21. The percentage of trips made by riders from the lowest household income level is estimated to be 23.1%, compared to 17.3% under the current fare policy.

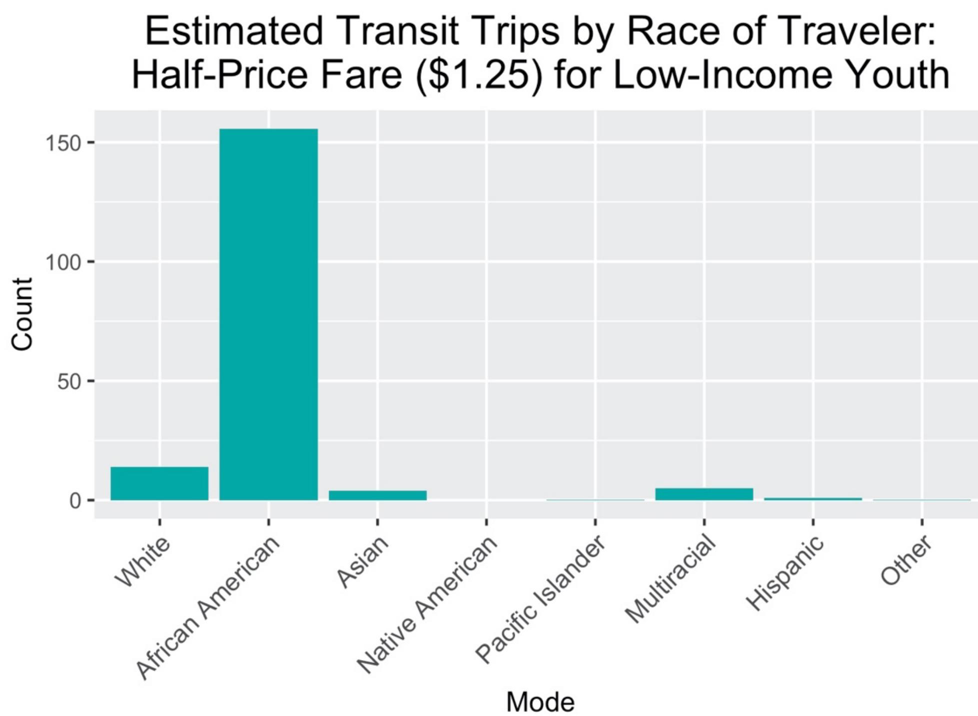

Figure 20: *Estimated transit trips by race of traveler with half-price fare for low-income youth (weighted N=11,278)*

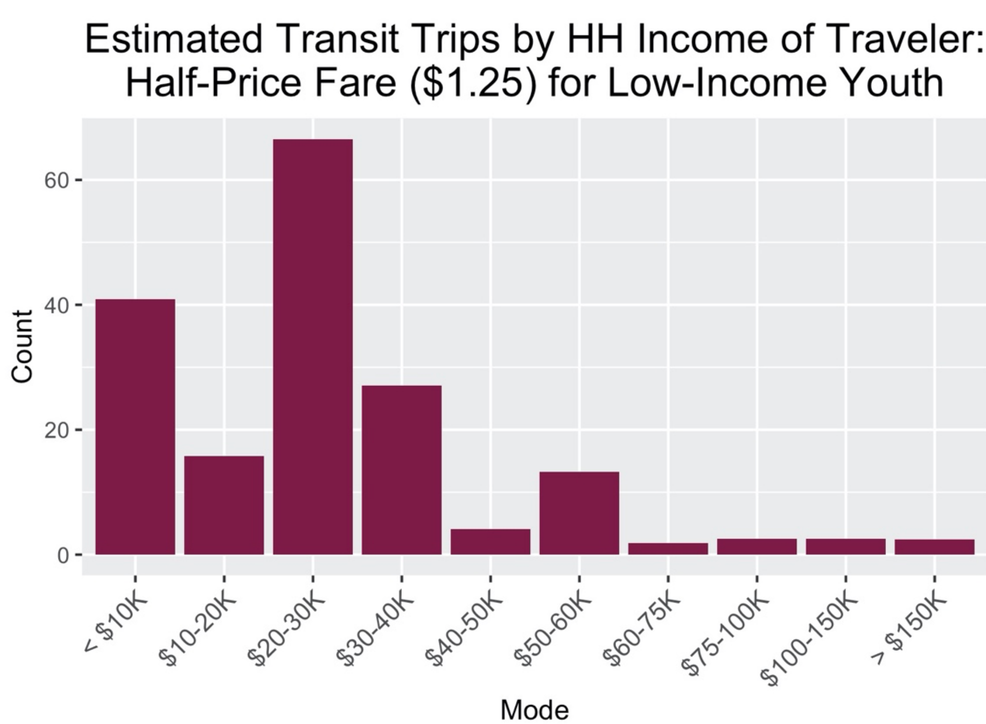

Figure 21: *Estimated transit trips by HH income of traveler with half-price fare for low-income youth (weighted N=11,278)*

5.3.5. *Discounted Fare for Low-Income Youth: $1*

The next hypothetical fare policy tested would offer discounted fares of $1 to students who qualify for free or reduced-price lunch and require other youth to pay the full fare of $2.50. This policy would result in an estimated 194.0 trips per day, which accounts for 1.72% of the total number of trips when weighted to match the population. This would result in a 72% increase in ridership over the estimated ridership under the current policy. This policy further increases the share of trips made by riders from the lowest income category to 23.8% from 17.3% under the current fare, as shown in Figure 22. As before, no notable changes in the share of trips made by travelers of each race are observed under this policy compared to the current policy. The estimated farebox revenue under this policy is $235.82 per day, or $86,440.97 per year.

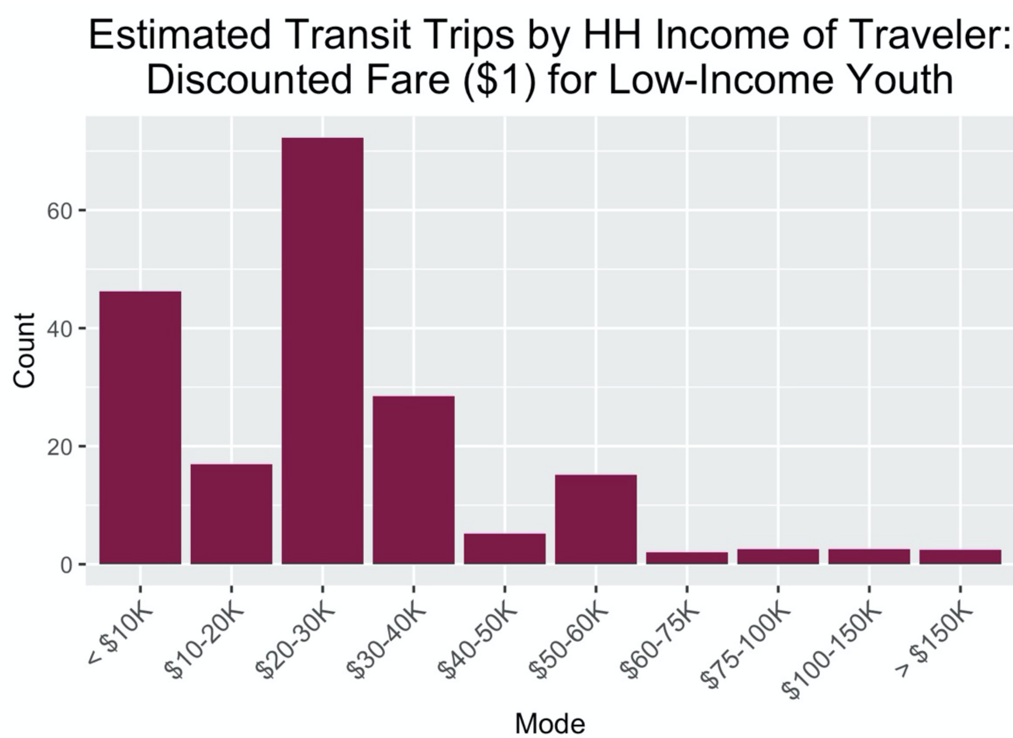

Figure 22: *Estimated transit trips by HH income of traveler with discounted ($1) fare for low-income youth (weighted N=11,278)*

5.3.6. Free Fare for Low-Income Youth

The final fare policy evaluated would offer free transit access to low-income students who qualify for free and reduced-price lunch but require other youth to pay the full fare of $2.50. This policy is estimated to result in 279.1 youth transit trips, the second-largest ridership estimate across all policies tested, behind a free fare policy for all youth. This represents a 148% increase in ridership over the current fare and accounts for 2.47% of all non-school youth trips in the study. Because a large number of these trips would charge no fare, the estimated daily farebox revenue from these trips is only $71.31, which translates to $26,026.74 per year. Again, we see no notable influence on the population of estimated transit riders when examined by race, but this policy does have the potential to attract a larger number of low-income riders, as we would expect. The share of trips made by riders from the three lowest income levels is predicted to increase from 65.9% under the current fare policy to 70.3% under a policy that offers free fare to low-income youth (Figure 23).

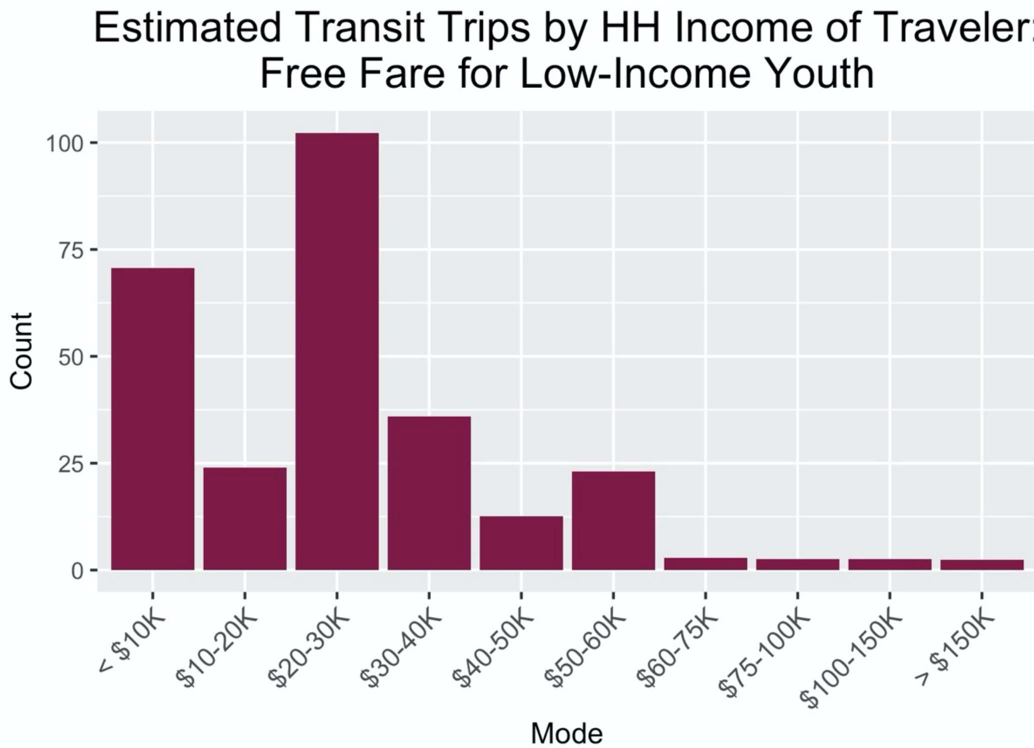

Figure 23: *Estimated transit trips by HH income of traveler with free fare for low-income youth (weighted N=11,278)*

5.4 Summary of Results

The results of all six hypothetical youth fare policies tested, as well as MARTA's current and past fare policies, are presented in Table 4. As described in the above sections, none of the policies appears to attract riders of one racial group over another, but many of the policies show the potential to attract a larger number of low-income riders than is estimated under the current policy. In terms of revenue, the $2 fare available at the time of the 2011 ARC Regional Household Travel Survey is estimated to result in the highest daily farebox revenue from non-school youth trips, balancing the lower fare price with higher ridership relative to the current policy. Figure 24 shows how the daily farebox revenue estimates compare across all policies.

In terms of ridership, offering free youth fares would predictably lead to the greatest increase in youth transit ridership (Figure 25). However, other fare policies showed the potential to substantially increase ridership with a much smaller loss in revenue. For example, offering a $1 fare for all youth would increase ridership by 116% while only decreasing revenue by 13.5% compared to the current fare policy. Similarly, a half-price youth fare would increase ridership by 91% but only result in a 4.6% loss in farebox revenue. As described in Chapter 2, increased youth transit ridership has the potential to improve the physical health and social lives of children and teens, as well as the environmental health of the community. Therefore, on a societal level, these benefits could far outweigh the small loss in farebox revenue. From MARTA's perspective, increased youth ridership also has the potential to lead to increased adult ridership in the future as these children age and eventually pay full fare (Long et al. 2019). Furthermore, many of these children could be accompanied on MARTA by parents or other adult caretakers who may have otherwise driven and whose full fare would more than offset the loss in revenue resulting from the reduced youth fare. Further analysis is needed to understand the joint travel behavior and mode choices of households and estimate the effect that accompanying travelers could have on farebox revenue from youth transit trips. In addition, the application of the model to these scenarios only predicts how the mode shares of this fixed set of trips would change with different fares; it does not account for the fact that lower fares will likely prompt youth to make *additional* transit trips that may also be accompanied by other travelers. Overall, the results show that a discounted youth fare of $1 or $1.25 has the potential to substantially increase MARTA's youth ridership, the external benefits of which would likely far outweigh the relatively small loss in farebox revenue. Even merely rolling back the youth fare to $2, the universal fare in 2011, would increase both youth ridership (by 30.5%) and farebox revenue (by 4.4%) compared to the current fare of $2.50.

Table 4: *Summary of all fare policies evaluated*

Fare Policy	Estimated Daily Ridership	Transit Mode Share	Change in Daily Farebox Revenue (based on current estimated revenue)
Free for all youth trips	398.78	3.54%	-100%
Free for low-income youth; others pay regular fare ($2.50)	279.13	2.47%	-74.5%
$1 for all youth trips	243.72	2.16%	-13.5%
$1 for low-income youth; others pay regular fare ($2.50)	194.04	1.72%	-16.0%
Half-price ($1.25) for all youth trips	215.18	1.91%	-4.6%
Half-price for low-income youth; others pay regular fare ($2.50)	177.26	1.57%	-8.8%
$2 (fare at the time of survey)	147.10	1.30%	+4.4%
$2.50 (current fare)	112.76	1.00%	0%

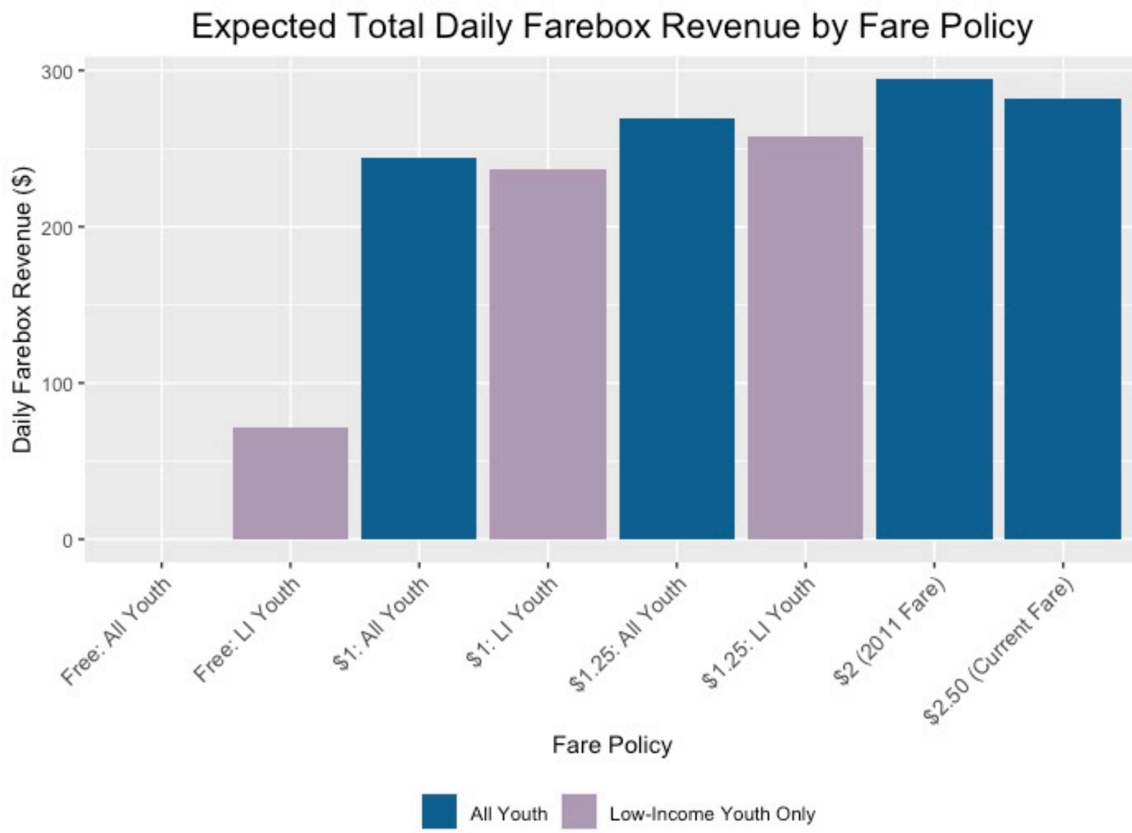

Figure 24: *Estimated daily farebox revenue for each policy studied (weighted N=11,278)*

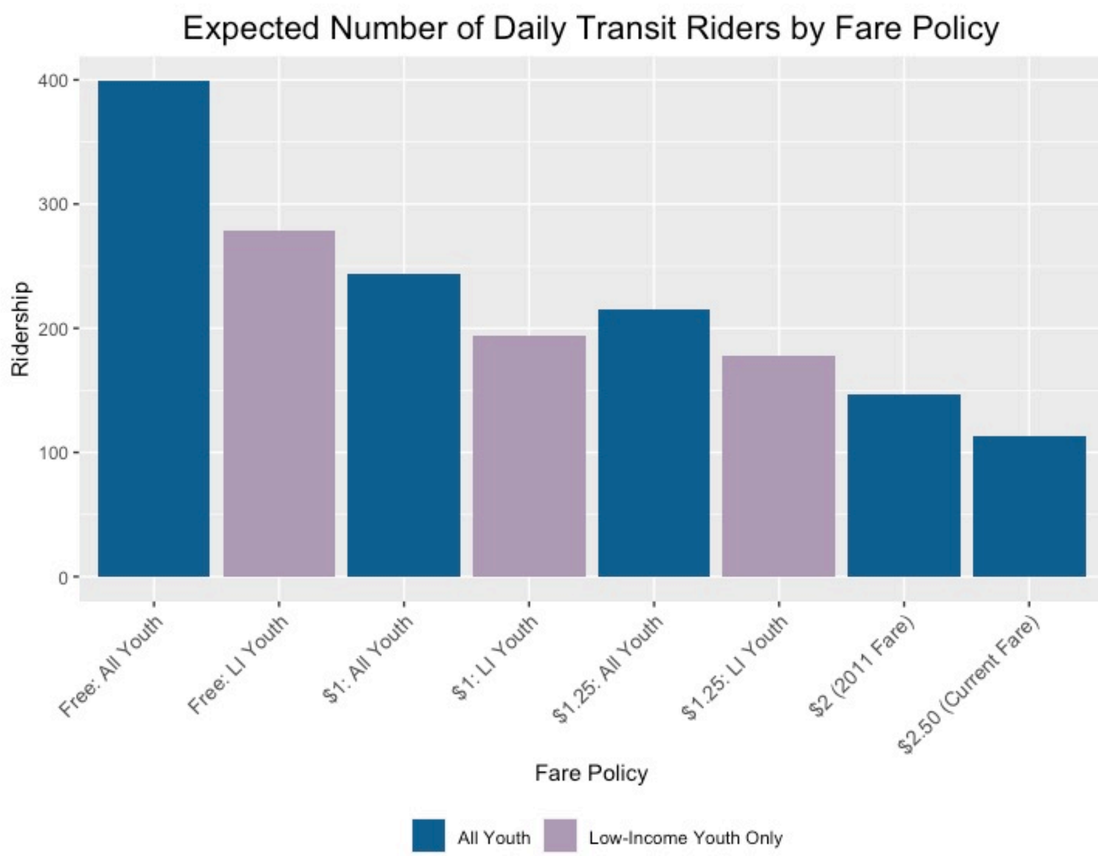

Figure 25: *Estimated daily youth transit ridership for non-school trips by fare policy (weighted N=11,278)*

CHAPTER 6: POLICY RECOMMENDATIONS AND IMPLEMENTATION

Based on the results of the policy evaluation, MARTA could increase youth ridership by offering a discounted youth fare of $1 or $1.25 and only experience a relatively small loss in revenue. These policies could have far-reaching benefits to youth, their families, and their communities. It is recommended that MARTA give further consideration to such a policy, including identifying potential funding sources, developing a process for registration and use of youth transit passes, and marketing this new policy. The sections below provide a starting point for this process and discuss factors besides fare policy that should be considered when attempting to attract more young transit riders.

6.1 Recommendations for Implementation

The youth transit fare policies of other large transit agencies and their methods of implementation, which are described in Chapter 3, provide a helpful guide for determining how MARTA might implement a reduced-price youth fare. Similar to the process used by the Los Angeles County Metropolitan Transit Authority and the San Francisco Municipal Transit Agency, youth applying for reduced fares on MARTA could register for a youth Breeze card via an online application or in person at a MARTA RideStore by providing proof that they are 18 years old or younger (Los Angeles County Metropolitan Transportation Authority 2019b; Metropolitan Transportation Commission 2020; MARTA n.d.). Although some agencies administer their youth fare programs through schools, the growing number of logistical challenges that schools are facing amid the COVID-19 pandemic, and will likely continue to face in the coming years, would make such a partnership challenging in the near future (District Department of Transportation 2020b). However, if they have the capacity, schools near MARTA routes, whose students are among the most likely to benefit from a discounted youth fare, could prove invaluable in marketing the new policy. Updated fare listings and advertisements at bus stops and in transit stations will be useful to inform existing riders but reaching new riders will be crucial to producing an increase in youth ridership. Schools, community organizations, and social media should all be considered when developing a marketing strategy for the new fare.

6.2 Additional Considerations

Although the policy evaluations described in Chapter 5 show that a discounted youth fare has the potential to increase youth ridership on MARTA, the largest mode share is still estimated to be under 5%. This result indicates that changes other than fare discounts are needed before any drastic increases in youth ridership will be seen. The following sections describe two such challenges: service availability and parent safety concerns.

6.2.1. Service Availability

One of the largest barriers to youth MARTA ridership is simply the lack of service availability at either their origin, destination, or both. Of the 15,910 cases in the survey data, which includes both school and non-school trips, the OpenTripPlanner tool was only able to find a feasible transit route for 3,354 of them (*OpenTripPlanner* (version 1.0) 2016). The maximum weighted mode share of transit under these conditions is 23.4%, compared to the existing mode share of auto modes in the data, which is 72.8% including both drivers and passengers. Figure 26 and Figure 27 display this trend geographically, showing the number of trips that start and end in each TAZ relative to MARTA's routes. Although the TAZs in the northeast portion of MARTA's service area produce or attract a large number of youth trips, most of the trips in the data begin or end in the suburban TAZs outside MARTA's service area. It is unreasonable to extend service to the entire region, but MARTA may be able to serve additional young riders by offering first and last mile service or partnering with other organizations to do so.

6.2.2. Parent Safety Concerns

As described in Chapter 2, one of the primary reasons that parents choose to chauffeur their children rather than allowing them to travel independently is concern for their safety (Fotel and Thomsen 2003; Sener, Lee, and Sidharthan 2019; Carver, Timperio, and Crawford 2013). Though the influence of parents was not explicitly considered in the model, it is likely that these concerns played a role in determining children's mode choice. Perceptions of safety are difficult to quantify and often don't align with the true chances of danger in a situation, making it challenging to address these concerns. However, previous research has shown that parents monitor the safety of their children's travel in ways other than simply chauffeuring them, such as by tracking the location of the child's cell phone or asking the child to call upon reaching a destination (Fotel and Thomsen 2003). With the increasing sophistication of location tracking technology and smart card fare payments, the potential may even exist for parents to track their children's transit travel via the times and locations at which they scan their transit pass.

Another possible way to increase parent perceptions of their children's safety on transit is the coordination of travel with other children or families. A similar strategy has been used to encourage walking to school through the creation of “walking school buses” (National Center for Safe Routes to School n.d.). Walking school buses are groups of children who live along the same route to school and walk to school with a parent or other adult supervisor. They alleviate some parents’ concerns for their children’s safety while eliminating the need for parents to be part of their child’s journey every day (National Center for Safe Routes to School n.d.). The same principles could apply to youth transit travel as well. Whether formally or informally, coordinating travel with a group of friends or with other adult supervisors could improve children’s safety, both perceived and real, when traveling on public transit.

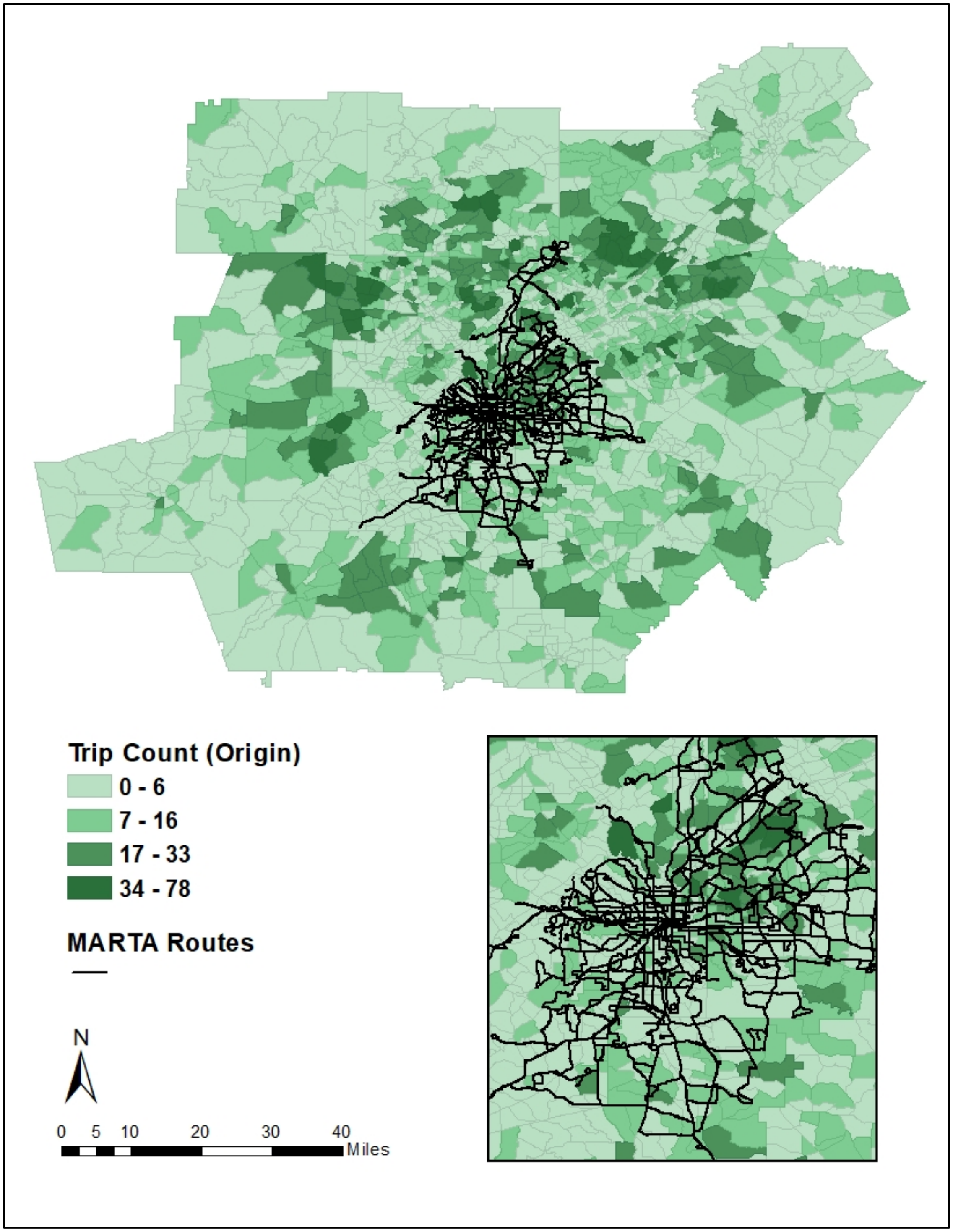

Figure 26: *Density of youth trip origins by TAZ*

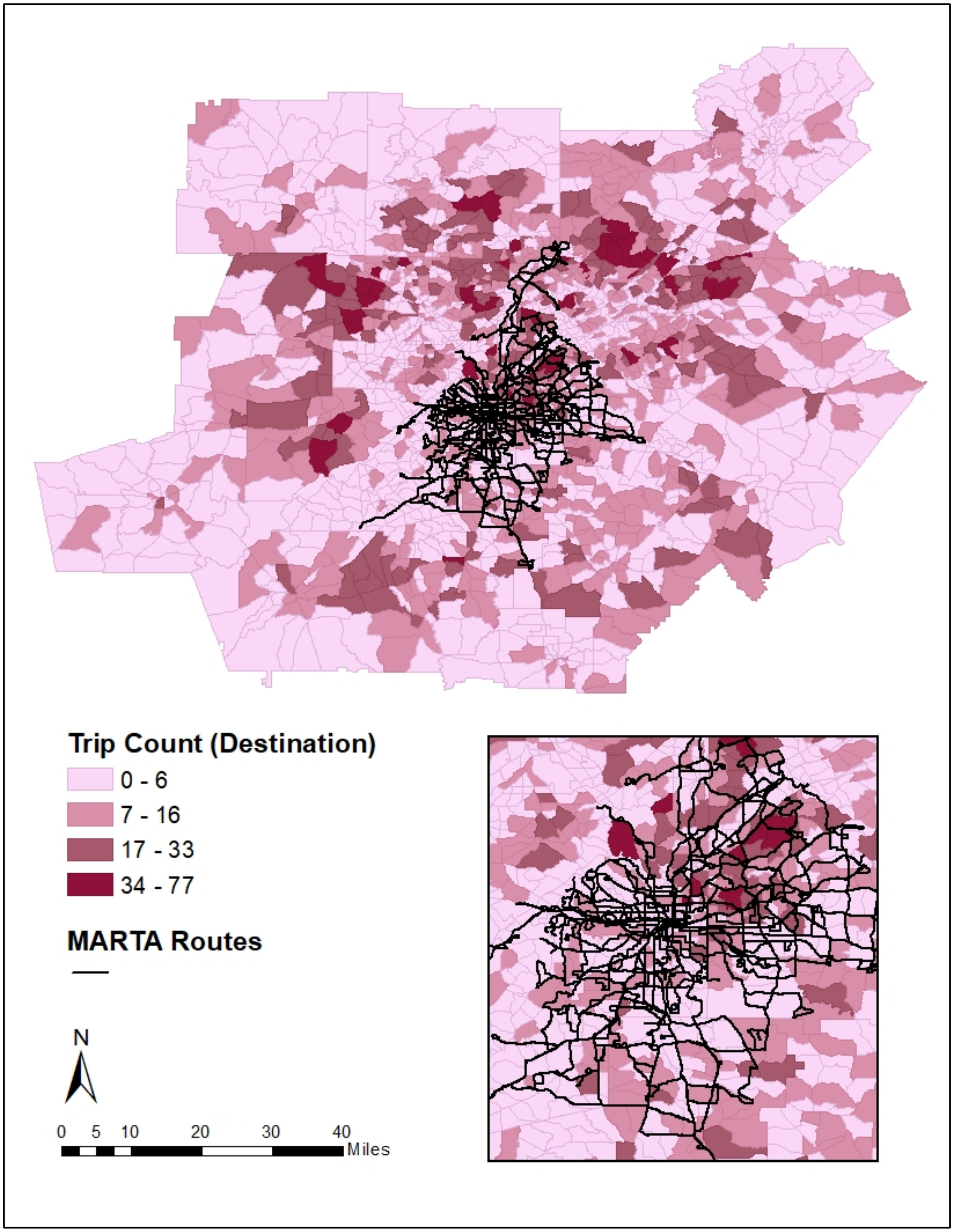

Figure 27: *Density of youth trip destinations by TAZ*

CHAPTER 7: CONCLUSION

In the United States and in much of the world, the share of children and teens traveling independently has been declining for decades as parents choose to chauffeur their children (McDonald 2005a). This trend is observed in the Atlanta region as well, where over 60% of trips made by individuals 18 and under were made as auto passengers. As traffic congestion continues to worsen, the Atlanta Regional Commission has noted the importance of encouraging travel via other more sustainable modes and the benefits this could have for the environmental and economic health of the region (Atlanta Regional Commission 2013). However, the current fare structure on MARTA does not incentivize transit travel for youth or families traveling with children, as children over approximately 6 years old are required to pay the full adult fare to travel on MARTA (MARTA n.d.). The research presented here has shown that offering a free or reduced-price youth fare on MARTA has the potential to incentivize a mode shift from youth and families currently traveling by car and could create new travel possibilities for families who don't have access to a vehicle.

The model developed for this research estimated that a $1 youth fare would more than double the number of youth trips made on MARTA for non-school purposes. Although this increased ridership would not be enough to offset the loss in farebox revenue from each trip, the relatively small revenue loss in the short term could still pay off for MARTA in the long term, as individuals who take transit as children and teens may be more likely to continue to do so in adulthood (Long et al. 2019; Bou Mjahed, Frei, and Mahmassani 2015; Thigpen and Handy 2018). It is also possible that this revenue loss would be smaller than estimated, as this model did not account for the adults who may accompany their children on transit if the cost were reduced but who currently choose to travel by car or rideshare, such as Uber and Lyft. For example, a family with two adults and two children may currently forgo transit because the costs of either parking their own car or traveling via rideshare are less than the cost of four full fare MARTA passes. However, if the children's fare were reduced, the option of buying two full fare passes and two reduced-price youth passes may be more appealing than driving or rideshare. Even without accounting for the revenue from accompanying adults, offering a youth fare of $2, the regular fare at the time of the survey, is predicted to lead to increases in both youth ridership and farebox revenue.

Outside of the financial costs and benefits to MARTA, increasing youth transit ridership through a discounted fare could offer additional benefits to these children and teens and their communities. Previous research has shown that children with greater independent mobility often have improved physical health and knowledge of their environment, as well as increased opportunities to socialize with their peers (Jones et al. 2012; Besser and Dannenberg 2005; Rissotto and Tonucci 2002). For the larger community, incentivizing a shift from automobiles to transit would improve the environment and economy of the region. Although the model showed that a discounted youth fare on MARTA has the potential to attract more youth ridership, the transit mode share under even a free fare policy was still less than 5%. A new fare policy should therefore be just one part of a larger effort to attract youth ridership, including improved service availability and safety, if MARTA is to capture a substantial share of total youth trips.

The results presented here provide a strong starting point for understanding the potential of a MARTA youth fare, but further work is necessary to more accurately account for the many factors that may influence youth transit ridership. As mentioned above, a model that better accounts for adults who may accompany children on transit would allow for a more accurate estimate of the impacts that a discounted youth fare would have on farebox revenue. Such an analysis would likely need to model mode choice decisions for the entire household, accounting for the interactions in mode choices between household members. Another key element missing from this work was an evaluation of the impact that a youth fare would have on school trips. Because the survey data did not include any trips taken on transit for the purpose of attending school, it is difficult to model the utility of this alternative for school trips. However, future work could develop a mode choice model for these trips based on more thorough data or could estimate the coefficients of a transit utility function based on the coefficients of other alternatives in the model.

Despite these possible improvements, the analysis presented here still provides helpful estimates of the potential that a discounted youth fare has to increase ridership on MARTA. As city and regional officials create plans to incentivize travel via sustainable modes and decrease traffic congestion, a MARTA youth fare, and the benefits it could create for the physical, environmental, and economic health of the region, should be given strong consideration.

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